The Consumption Response to Protectionism*

Chen Lin[†], Hongyu Shan[‡], and Da Tian[§]

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Abstract

Despite policy aims to support income and employment, we show that U.S. households in counties more exposed to protective tariffs spend less over time. Spending declines coincide with falling wages and persist after accounting for exposure to pass-through and retaliatory tariffs. Reductions in both quantities and prices point to a demand-driven contraction. Effects are stronger when tariffs target capital rather than consumption goods, and are concentrated among working-class Americans, who subsequently cut discretionary spending. We underscore the vertical integration of U.S. and Chinese firms within tariff-targeted industries. Protectionism does not benefit domestic labor market and may risk local household welfare.

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[†]Stelux Professor in Finance, University of Hong Kong, Hong Kong SAR, China. Email: chenlin1@hku.hk.

[‡]Associate Professor of Finance, China Europe International Business School (CEIBS). Email: hongyushan@ceibs.edu.

[§]Corresponding Author. Assistant Professor of Finance, School of Finance, Nankai University. Email: tianda@nankai.edu.cn.

1 Introduction

The re-election of President Donald Trump on November 5, 2024, followed by the announcement of the most sweeping tariff increases since the 1930 Smoot-Hawley Tariff Act, has ignited broad concerns over the resurgence and intensification of protectionist trade policies. The trade disputes initiated by the Trump Administration - targeting China, the European Union, and other major trading partners - represented a pivotal shift in the trajectory of global trade. These policy shifts carry far-reaching geopolitical and economic implications, with measurable spillovers into both the real economy and financial markets.

While protective trade policies are often introduced with the aim of restoring income and generating employment, their impact on the welfare of domestic households remains contentious. Classic theories of comparative advantage predict that reciprocal tariff impositions lead to production inefficiencies, raising costs for import-dependent firms and ultimately burdening their employees (Hong and Li, 2017; Fajgelbaum et al., 2020; Amiti, Redding, and Weinstein, 2020). Indeed, anecdotal evidence suggests that domestic workers often bear the brunt of such measures: companies such as H&P, Alcoa, and Mattel have publicly linked large-scale layoffs to tariffs on electronics, aluminum, and toys, respectively, lamenting that the very policies intended to shield their industries failed to offer meaningful protection[1][2][3]. Nevertheless, proponents contend that elevated tariffs can mitigate the so-called *China Shock* — the adverse effects of surging Chinese import competition on U.S. manufacturing employment and firm viability (Autor, Dorn, and Hanson, 2013). Supporting this view, Honda has reportedly relocated Civic production from Mexico to Indiana in response to proposed

[1] Connor Hart, "HPE to Eliminate 2,500 Jobs as Tariffs Hurt Fiscal Outlook", *The Wall Street Journal*, March 6, 2025. https://www.wsj.com/business/earnings/hpes-fiscal-outlook-hurt-by-tariffs-server-execution-problems-cfo-says-fe3ac254

[2] Elisabeth Buchwald, "Trump's aluminum tariffs could cost 100,000 American jobs, US industry leader warns", *CNN*, February 25, 2025. https://www.cnn.com/2025/02/25/economy/trump-aluminum-tariffs-job-loss.

[3] Stephen Council,"Calif. toy giant lays off staff after CEO touts business strength", *SFGATE*, March 18, 2025. https://www.sfgate.com/la/article/mattel-lays-off-trump-tariffs-20228483.php.

Auto import tariffs, potentially boosting domestic employment and household wealth[4]. Ultimately, the aggregate and net welfare effects of these trade interventions remain ambiguous (Amiti, Redding, and Weinstein, 2019; Fajgelbaum and Khandelwal, 2022), and considerable debate persists over how the trade shocks are distributed across different segments of the economy (Cavallo et al., 2021; Jiao et al., 2022; Huang et al., 2023; Flaaen and Pierce, 2024).

This study examines the impact of protective tariffs on U.S. consumers by analyzing highly granular, micro-level consumption patterns. The trade war, partially motivated by political objectives (Grossman and Helpman, 1995; Rodrik, 2017; Fetzer and Schwarz, 2021; Che et al., 2022), was intended to enhance the living standards of households — particularly those in regions disproportionately affected by Chinese import competition. We investigate the effects of these tariffs on consumer welfare through the lens of household consumption, extending our analysis to five quarters post-initiation of the U.S.-China trade war, to determine whether the anticipated benefits of import tariffs have materialized.

From a theoretical perspective, protective tariffs can affect household consumption through both price (supply) and income (demand) channels. Specifically, there are four distinct yet interrelated mechanisms. The first is related to the price effect, while the remaining three pertain to income effects stemming from both import tariffs and retaliatory tariffs. First, import tariffs tend to increase retail prices and reduce product availability. A key question for policymakers and economists alike is the extent to which the tariff-induced price increases are absorbed by consumers - leading to reduction in household consumption. Much of the existing literature on trade wars has focused on this critical issue of tariff pass-through (Amiti, Redding, and Weinstein, 2019, 2020; Fajgelbaum et al., 2020; Cavallo et al., 2021; Cavallo, Llamas, and Vazquez, 2025; Jiao et al., 2022; Ma et al., 2024). Second, retaliatory tariffs imposed by foreign countries in response to U.S. protectionism may reduce income and, subsequently, consumption (Waugh, 2019; Carter and Steinbach, 2020). Third, import

[4] Maki Shiraki, "Honda to produce next Civic in Indiana, not Mexico, due to US tariffs, sources say", *Reuters*, March 4, 2025. https://www.reuters.com/business/autos-transportation/honda-produce-next-civic-indiana-not-mexico-due-us-tariffs-sources-say-2025-03-03/

tariffs could lead to a positive income effect by protecting domestic industries (Autor, Dorn, and Hanson, 2013; Pierce and Schott, 2016; Caliendo, Dvorkin, and Parro, 2019; Autor, Dorn, and Hanson, 2021), thereby stimulating consumption. Finally, as a consequence of increased import tariffs, consumption can decrease due to a negative income shock driven by the rising costs of imported inputs for domestic companies (Barattieri and Cacciatore, 2023; Bown et al., 2021; Flaaen and Pierce, 2024; Handley, Kamal, and Monarch, 2025; Grossman, Helpman, and Redding, 2024), which ripples through the labor market and ultimately burdens employed households. This study is among the first to rigorously assess and disentangle the conflicting predictions of the latter two channels, while also controlling for the well-documented effects of the first (pass-through) and second (retaliatory tariffs) mechanisms.

To address this question, we utilize data from the Nielsen Consumer Panel, which provides a comprehensive record of shopping behavior for 40,000 to 60,000 U.S. households, continuously surveyed by NielsenIQ from 2004 to 2019. This dataset offers detailed information on household consumption at the household, trip, and product levels, including precise dates of shopping trips and detailed product information for all items purchased. The granularity of this data allows us to observe product-level purchasing prices and quantities for frequent shopping trips, thereby enabling a nuanced analysis of micro-level consumption responses to the trade war's developments.

Our analysis indicates that, in the aftermath of the trade war, households in the treatment group — those with the highest exposure to import tariffs — exhibited a statistically and economically significant decline in aggregate spending relative to households in the control group. Specifically, quarterly spending fell by approximately $14, or 1.2 percent. To contextualize, this magnitude is substantial given that the average household quarterly spending in our sample is $1,342, and the average annual growth rate of Personal Consumption Expenditures per capita between 2008 and 2017 was 2.34 percent. We define treatment and control groups based on differential exposure to import tariffs while holding exposure to retaliatory tariffs relatively the same, thereby isolating the effect of the import-side policy shock (i.e., controlling for the second mechanism). The observed decline in consumption suggests that the anticipated welfare gains from protective tariffs did not materialize. On the contrary, households in counties ostensibly shielded from Chinese import competition experienced a relative deterioration in economic well-being. These findings are consistent with Flaaen and Pierce (2024), who document that counties more exposed to rising import tariffs suffered employment losses, and with Blanchard, Bown, and Chor (2024), who document that during the 2018 midterm election, the Republican Party received limited electoral gains in counties that received greater U.S. tariff protection. As a robustness check, we implement a continuous Difference-in-Differences specification, rather than partitioning households into discrete treatment and control groups. The main results remain both economically and statistically significant under this alternative empirical framework.

While these results suggest a negative relationship between changes in protective tariff exposure and household consumption, attributing this decline solely to a demand-side response is complicated by the well-documented pass-through effects of tariffs (the first mechanism). Specifically, import tariffs may compress retail margins, thereby limiting product availability, or increase retail prices, leading to a contraction in supply (Amiti, Redding, and Weinstein, 2019; Ma et al., 2024). Both scenarios would result in a marked reduction in household consumption.

We contend that the observed effects are not entirely attributable to tariff pass-through for two reasons. First, we conduct a product-level analysis that tracks changes in (1) the total consumption, (2) the quantity purchased, and (3) the unit price of the *same* goods consumed by the *same* household over the course of the trade war. By focusing on the consumption patterns of the same products, we demonstrate that the reduction in overall spending is not merely a result of changes in the composition of the shopping basket. More importantly, the simultaneous declines in both quantity and price of the same product consumed by the same household suggest the presence of a demand-side effect that operates independently of the pass-through impacts. Second, we incorporate $Product \times Time$ fixed effects in our within-household product analysis, which allows us to fully account for any potential supply-side variations at a highly granular level.

To validate the hypothesis that the observed reduction in consumption is driven by a contraction in demand, we examine labor market outcomes in the treatment regions in conjunction with spending patterns. We start by calculating the average weekly wage for each county and observe that, subsequent to the trade war, counties in the treatment group experience a decrease of \$10.26 in weekly wages compared to the control group. This decline in the intensive margin of the local labor market, amounting to a 1.96% reduction in the year-on-year growth rate, is both statistically and economically significant. Compared with non-tradable sectors, wages in tradable sectors experienced a more pronounced decrease. In addition, we analyze changes in employment across counties. While the coefficient points to a negative contraction of the extensive margin of the labor market, the result does not reach statistical significance, likely due to labor market rigidities that impede swift adjustment to new economic conditions (Beck et al., 2023). These findings collectively suggest that the higher import tariffs imposed post-trade war have adversely affected labor market conditions in the treatment areas, highlighting the income channel as a critical factor driving the observed reduction in consumption.

Further cross-sectional analysis indicates that the income shock induced by the trade war was disproportionately borne by working-class households. The effects are not statistically significant for younger households who have recently entered the labor market or for older households who are already retired. The most pronounced consumption responses are observed among middle-aged, upper-middle-class households. These households adjust their consumption primarily by curbing expenditures on discretionary items - such as health and beauty products, alcoholic beverages, and confectioneries - while preserving spending on essential goods including dairy products, fresh produce, and meat. Although spending on durable goods, such as household appliances, also declines, the magnitude of this reduction is smaller relative to that observed for discretionary categories. This heterogeneous adjustment highlights the concentrated impact of the trade war on non-essential consumption, with expenditures on necessities remaining comparatively stable.

The remainder of this study examines the underlying mechanisms of this income shock. The existing *China Shock* literature has emphasized that China's integration into the WTO had adverse effects on domestic households' quality of life in directly competing industries. A natural expectation is that the welfare effects of trade integration and its subsequent reversal would be symmetric — that is, the recent unwinding of trade relationships should mitigate the earlier negative impacts. However, our findings contradict this expectation. We argue that this asymmetry reflects the evolving trade relationship between the U.S. and China. First, many U.S. firms have offshored production to China, retaining brand ownership and design capabilities while outsourcing manufacturing. The importation of these goods, such as apparel, footwear, and toys, is often classified as intra-industry trade by the parent firm. Additionally, there has been a significant shift in the composition of imports from China, from consumption goods to intermediate and capital goods. U.S. firms across various sectors now rely heavily on upstream inputs from Chinese supply chains; for example, the pharmaceutical industry depends on key starting materials and Active Pharmaceutical Ingredients (APIs) sourced from China. While the initial phase of trade integration primarily exposed domestic industries to *horizontal* competition from Chinese imports, the more recent phase of trade unwinding has instead contributed to the fragmentation of *vertical* supply chains integrated within the same industry.

In this context, Wang et al. (2018) highlight a supply-chain perspective that reveals Chinese imports can, in fact, bolster local employment and wages. Using French data, Aghion et al. (2024) reach a similar conclusion. During the trade war, many of these inputs from China were subjected to substantial tariff hikes (Amiti, Redding, and Weinstein, 2019; Flaaen and Pierce, 2024; Grossman, Helpman, and Redding, 2024; Handley, Kamal, and Monarch, 2025). Although, in theory, the burden of tariffs is shared between U.S. importers and Chinese exporters depending on market power, empirical evidence on rent-sharing suggests that U.S. firms absorb a significant portion of the tariff burden (Amiti, Redding, and Weinstein, 2019, 2020; Fajgelbaum et al., 2020; Cavallo et al., 2021; Jiao et al., 2022). Consequently, higher import tariffs can increase input costs for U.S. firms, transmitting negative shocks to the labor market through wage adjustments for affected households. This income shock forces workers to adjust their consumption behavior, and the resulting contraction in consumption may further amplify the negative effects in the labor market (Giroud and Mueller, 2017). Moreover, the negative shock is unlikely to be confined to local economies; it may be transmitted to other regions through various networks within and between firms (Giroud and Mueller, 2019; Giroud et al., 2024).

To further investigate this potential asymmetry from the perspective of vertical integration, we examine whether our findings are sensitive to the distribution of tariffs within the targeted industry. We argue that the effects should be more pronounced if protective tariffs are, within the same industry, imposed on capital and intermediate goods rather than on consumption goods. This expectation builds on the assumption that, on average, U.S. firms are positioned closer to the market or consumption end of the production chain within their respective industries. While we acknowledge that we do not directly observe individual household wages, our findings support the hypothesis that import tariffs increase production costs for domestic firms, which ripple through the labor market, and ultimately shape the consumption behaviors of households through income shocks.

Our study contributes to three strands of literature at the intersection of finance and international economics. First, it relates to the growing body of research that examines the determinants of household consumption behavior (Gomes, Haliassos, and Ramadorai, 2021). Previous studies have shown that household spending decisions are shaped by a variety of factors, including the adoption of digital payment technologies (Agarwal et al., 2024), macroeconomic uncertainty (Coibion et al., 2024), socio-political identity (Agarwal et al., 2020), home ownership (Agarwal and Qian, 2017), tax policy (Agarwal, Ghosh, and Zhang, 2024), and social experiences (Agarwal, Qian, and Zou, 2021; D'Acunto, Rossi, and Weber, 2024). We contribute to this literature by introducing trade policy as an additional, economically meaningful determinant of household consumption. In particular, we examine how protectionist measures, designed to preserve domestic wealth and income, affect household behavior in product markets.

The second addresses the competitive effects of trade integration and their implications for social welfare. A substantial body of work has documented the displacement effects associated with increased import competition, particularly from China, highlighting the declines in local welfare outcomes (Autor, Dorn, and Hanson, 2013; Pierce and Schott, 2016; Caliendo, Dvorkin, and Parro, 2019; Autor, Dorn, and Hanson, 2021). In addition to these welfare impacts, increased competition has also reshaped firms' behavior, influencing their financing decisions, investment strategies, corporate governance, and innovation activities (Fresard, 2010; Giroud and Mueller, 2010; Valta, 2012; Xu, 2012; Dasgupta, Li, and Wang, 2018; Hombert and Matray, 2018; Hoberg, Li, and Phillips, 2019; Mayordomo and Rachedi, 2022; Lie and Yang, 2023; Hankins, Momeni Shahraki, and Sovich, 2023; Martin and Otto, 2024). In particular, Barrot et al. (2022) provide evidence that household debt levels increased after China's entry into the World Trade Organization. Our findings contribute to this literature by showing that the reversal of free trade policies does not necessarily mitigate these negative effects.

Additionally, our paper contributes to the expanding literature on the effects of the U.S.-China trade war on U.S. consumers. Much of the existing research has concentrated on retaliatory tariffs (Waugh, 2019) or on supply-side factors by assessing pass-through effects on household spending (Amiti et al., 2020; Fajgelbaum et al., 2020; Cavallo et al., 2021; Cavallo, Llamas, and Vazquez, 2025). Notably, Ma et al. (2024), using the same NielsenIQ database, investigates supply-side effects through both price and product variety channels, assessing their influence on the consumer cost of living. In contrast, our study addresses a distinct research question by shifting the focus to the demand-side consequences of protective tariffs. Specifically, we identify a novel income channel operating through vertically integrated industries, while carefully controlling for price pass-through and retaliatory tariff exposure. Our findings align with a broader literature documenting the adverse effects of the trade war through the disruption of established trade networks (Aghion et al., 2024; Baqaee and Malmberg, 2025; Bellora and Fontagné, 2020; Flaaen and Pierce, 2024; Handley, Kamal, and Monarch, 2025; Grossman, Helpman, and Redding, 2024).

2 Institutional Background

In this section, we provide a detailed review of the evolution of trade conflicts between the world's two largest economies — the United States and China (Section 2.1) — and assess their impact across industries (Section 2.2). These discussions are essential for establishing our identification strategy, particularly in defining the treatment household group and delineating the post-intervention period in our Difference-in-Differences (DiD) analysis.

2.1 The Development of the Trade War

The U.S.-China trade war escalated notably in 2018, following years of latent trade tensions. In 2017 and early 2018, the U.S. initiated investigations under Sections 201 (safeguards against import surges), 232 (national security), and 301 (unfair trade practices) of the Trade Act of 1974. These investigations targeted a wide array of products, including solar panels, washing machines, steel, aluminum, and China's trade and industrial policies. Notably, some of these measures were not exclusively directed at China, but also aimed at other trading partners.

On March 22, 2018, President Trump directed the U.S. Trade Representative (USTR) to propose tariffs on \$50–60 billion worth of Chinese goods under Section 301. On April 3, 2018, the USTR released a \$50 billion list targeting advanced technology sectors, such as aerospace, medical devices, and semiconductors. In immediate retaliation, China introduced its own \$50 billion list on April 4, 2018, targeting U.S. agricultural exports (e.g., soybeans, pork) and manufactured goods (e.g., automobiles, airplanes). Chinese importers subsequently halted purchases of major U.S. agricultural commodities, including soybeans,

On July 6, 2018, *Phase 1* of the trade war commenced, with both nations imposing 25% tariffs on \$34 billion of goods from their respective \$50 billion lists. On August 23, 2018, *Phase 2* began with 25% tariffs levied on the remaining \$16 billion of goods from both lists. On September 17, the U.S. introduced a new \$200 billion list, with an initial 10% tariff. In response, China announced its own list of \$60 billion, with tariffs ranging from 5% to 10%. These new tariffs were implemented on September 24, 2018, marking the *Phase 3* of the trade war.

On December 1, 2018, the U.S. postponed planned tariff increases, resulting in a temporary truce. Both parties agreed to work toward a negotiated settlement by March 2019. However, negotiations stalled in May 2019. On May 10, 2019, the U.S. raised its tariffs on \$200 billion worth of Chinese goods from 10% to 25%. China responded on June 1, 2019, imposing tariffs as high as 25% on \$60 billion worth of U.S. goods.

During the G20 Osaka Summit on June 29, 2019, both nations agreed to halt further tariff increases while resuming negotiations. However, the talks broke down again, and tensions reignited in August 2019 when the U.S. announced plans to impose 10% tariffs on an additional \$300 billion. On September 1, 2019, part of these new tariffs took effect: a 15% tariff on approximately \$112 billion of Chinese imports, while the remainder was postponed until December 15, 2019. In retaliation, China imposed additional tariffs on \$75 billion worth of U.S. goods, effective September 1, 2019.

On December 13, 2019, the U.S. and China reached a preliminary agreement, averting the planned December 15 tariff increases. The *U.S.-China Phase One Trade Deal* was signed on January 15, 2020, with China committing to increase purchases of U.S. goods.

Despite this, most of the tariffs imposed since 2018 remained in place throughout the Biden administration.[5]

2.2 The Distributional Impacts of the Trade War across Industries

In this subsection, we examine the economic impacts of the trade war across various industries. Figure A.1 illustrates the evolution of import and retaliatory (export)[6] tariff rates by industry, categorized according to the 3-digit NAICS code. The heat maps display tariff rates at six key points throughout the trade war: Pre-Trade War, 232 & 301 Investigation, Phase 1, Phase 2, Phase 3, and Trade Talk Fails. These maps reveal that industries such as Computer and Electronic Products, Machinery, Transportation Equipment, Electrical Equipment, and Appliances and Components were among the first to be targeted by the United States. In retaliation, China initially focused on industries such as Crop Production, Fishing and Hunting, Beverages and Tobacco, and Food.

Figure 1 presents three key metrics across industries in the context of the trade war: (1) the logarithmic change in industry-specific tariff rates, calculated using Equation 1; (2) pre-trade war tariff levels in December 2017 compared to those in December 2019; and (3) bilateral trade volumes by industry in 2017. The upper panel displays U.S. import tariffs on Chinese goods, while the lower panel shows Chinese tariffs on U.S. exports. Industries are ranked by the magnitude of their tariff changes, as defined by Equation 1.

$$Tariff\,Chg_s = log(1 + \tau_{s,post}) - log(1 + \tau_{s,201712}) \tag{1}$$

In Equation 1, $\tau_{s,201712}$ represents the December 2017 tariff rate for industry s (before

[5] The introduction of the progress of the trade war is from South China Morning Post (https://www.scmp.com/economy/global-economy/article/3177652/us-china-trade-war-timeline-key-dates-and-events-july-2018), Wikipedia (https://en.wikipedia.org/wiki/China-United_States_trade_war), and Waugh (2019).

[6] In this paper, we loosely refer to the retaliatory import tariffs levied by China on U.S. exports as "export tariffs," even though this term is not technically accurate.

the trade war), while $\tau_{s,\text{post}}$ denotes the average monthly tariff rate from July 2018 through December 2019.[7]

Figure 1 reveals that industries such as Oil and Gas Extraction, Furniture, Computer and Electronics, Paper, Machinery, Transportation, and Electrical Equipment experienced the most significant tariff increases during the trade war.

3 Data

3.1 NielsenIQ Retail Data

We utilize the NielsenIQ Homescan Consumer Panel (Consumer Panel) data, sourced from the Kilts-NielsenIQ Data Center at the University of Chicago Booth School of Business, to examine consumer purchasing behavior. This dataset meticulously tracks the shopping activities of approximately 40,000 to 60,000 U.S. households, continuously surveyed by NielsenIQ between 2004 and 2019. The participating households record all their purchases intended for personal and in-home use through in-home scanners or mobile applications. For each shopping trip, the dataset provides comprehensive transaction details for each product purchased, including information such as product identity, quantity, price, discounts, and the use of coupons. Products are identified by unique barcodes (UPCs) and categorized into distinct product groups. Figure 2 outlines the product groups analyzed in our study, with a predominant focus on items frequently purchased by households in grocery stores. The "DRY GROCERY" category, encompassing items such as candy, cookies, cereal, and other baked goods, represents the largest segment.

Beyond transaction data, the Consumer Panel offers extensive demographic information for each household, including household size, income, age, employment status, education level, and marital status. Notably, the surveyed households are geographically diverse and

[7] The logarithmic transformation is applied to accommodate industries with zero pre-trade war tariffs.

demographically representative. For instance, Figure 3 illustrates the geographic distribution of the surveyed households included in Nielson. The Consumer Panel is particularly valuable for our research as it allows us to leverage the high-frequency nature of shopping trips to examine the evolution of consumer purchasing behavior in response to the trade shocks.

3.2 Trade War Tariff Data

We construct three tariff-based measures to captures differential exposure to trade policy changes. The *Industry Tariff* varies at the Industry - Time level, the *Employment Adjusted Tariff* at the County - Time level, and the *Tariff Exposure* at the County level, which we use to classify the households into the treatment vs. control groups.

3.2.1 Industry Tariff

We construct industry-level tariffs by aggregating product-level tariffs from the Harmonized System (HS) to the three-digit NAICS classification. Since tariffs are administered at the border according to the HS classification, we first obtain HS 6-digit (HS6) tariff data and trade values. Specifically, we extract data on U.S. imports from China at the HS6 level for 2017 from the U.S. Census. Using the concordance provided by the U.S. Census, each HS6 product code is mapped to its corresponding NAICS 6-digit code. The three-digit NAICS industry-level tariff (denoted as $\tau_{s,t}$) is then computed as the trade volume-weighted sum of the HS6 tariffs within each three-digit NAICS industry (denoted as s).

3.2.2 Employment Adjusted Tariff

We follow Waugh (2019) to construct the Employment Adjusted (EMP-adjusted, hereafter) tariff levels for each county on a monthly basis.[8] The monthly EMP-adjusted import

[8] The data and methodology are downloaded from https://www.tradewartracker.com/, and we thank the author for kindly sharing the data publicly.

tariff level (denoted as $\tau_{c,t}$) for each county c is a function of the county's industry structure and each industry's import tariff rate $\tau_{s,t}$. The calculation follows Equation 2, where $L_{c,s,2017}$ is the county c's employment in sector s in 2017, and $L_{c,S,2017}$ is the county c's total private employment of all NAICS sectors. The local employment data is obtained from the Bureau of Labor Statistics. To avoid the forward-looking impact of the trade war on a country's labor market conditions, we follow Waugh (2019) to use the employment data in 2017 to calculate the weight.

$$\tau_{c,t} = \sum_{s \in S} \frac{L_{c,s,2017}}{L_{c,S,2017}} \tau_{s,t} \tag{2}$$

Note that $\tau_{c,t}$ evolves over time as the trade war unfolds, reflecting both temporal variation and cross-county heterogeneity in exposure to tariff changes. This heterogeneity arises from differences in industrial composition and employment structures across counties. For instance, a county with a larger share of its workforce employed in the steel sector would experience a greater impact from U.S.-imposed protective tariffs on steel, compared to a county with a smaller steel-related workforce. The methodology described thus far applies to the construction of the EMP-adjusted import tariff measure. The EMP-adjusted export tariff measure is constructed analogously by substituting import tariff rates in Equation 2 with export tariff rates.

Figure 4 plot the time-series characteristics of the EMP-adjusted import and export tariff levels across the U.S. We first calculate the EMP-adjusted tariff level at the county level that are defined in Equation 2, and then plot the average of all counties on the vertical axis. The time trends illustrated here corresponds to the milestones of the trade war described in Section 2.1. The average EMP-adjusted tariff levels were small and constant until the first quarter of 2018. Then there was a small increase due to the Section 232 or Section 301 investigations, and the response from China. In July 2018, the trade war erupted and escalated rapidly within a single quarter. In May 2019, the trade talks failed which brought another round of significant rise in tariffs. By the time when the truce was made in January 2020, the average EMP-adjusted import tariff level increased from 0.475% at the end of 2017 to 3.44%, an increase of 624%. The average EMP-adjusted export tariff level has increased from 1.093% to 3.745%, an increase of 243%.

3.2.3 Tariff Exposure

Finally, we construct the *Tariff Exposure* measures, which capture the local exposure to trade policy changes. Both import and export tariff exposures are computed at the county level and remain time-invariant. To assess the severity of the trade war's local impact, we compare pre- and post-trade war EMP-adjusted tariffs. The pre-trade war EMP-adjusted tariff for county c, denoted as $\tau_{\mathrm{c},201712}$, represents the county's EMP-adjusted tariff level as of December 2017. The post-trade war EMP-adjusted tariff is the average monthly EMP-adjusted tariff from July 2018 to December 2019, denoted as $\tau_{\mathrm{c,post}}$. The change in county-level EMP-adjusted import tariff level, $Import\ Exposure_c$, is calculated as:

$$Import\ Exposure_c = \log(1 + \tau_{\mathrm{c,post}}) - \log(1 + \tau_{\mathrm{c},201712}). \tag{3}$$

A similar measure, $Export\ Exposure_c$, captures changes in EMP-adjusted retaliatory tariffs, instead of the changes in EMP-adjusted import tariffs. Together, $Import\ Exposure_c$ and $Export\ Exposure_c$ reflect geographic variation in the severity of the trade war's local impacts. For example, a larger $Import\ Exposure_c$ indicates that county c has a larger share of its labor force employed in industries disproportionately affected by U.S. tariffs on Chinese imports, highlighting the heterogeneous exposure to protective trade policies across regions.

3.3 Summary of Statistics

Table 1 reports summary statistics for household consumption, trade war exposure measures, and a variety of the households socio-economic characteristics. We classify households into the treatment and control groups. The treatment group consists of households residing in counties with the highest levels of import exposure, while the control group comprises households in counties with the lowest exposure. Details on the construction of these groups are provided in Section 4.2.

Household spending data, denoted as *Quarterly Spending*, are sourced from Nielsen and aggregated to the quarterly level. Spending values are winsorized at the 1st and 99th percentiles to mitigate the influence of outliers. The dataset includes 103,320 household-quarter observations from 11,562 treatment-group households and 110,296 observations from 12,363 control-group households. The average quarterly spending in the treatment group is \$1,344 - approximately \$3 higher than that of the control group.

Pre-TW EMP-Adjusted Import Tariff and *Post-TW EMP-Adjusted Import Tariff* are EMP-adjusted import tariff level faced by each county, as defined in Equation 2. The Pre-TW measure corresponds to the EMP-adjusted tariff level as of December 2017 ($\tau_{c,201712}$), while the Post-TW measure is the average EMP-adjusted tariff level over the period from July 2018 to December 2019 ($\tau_{c,post}$). Both measures are expressed in percentage.

The sample includes 571 treatment counties and 993 control counties. In Panel A, the mean of *Pre-TW EMP-Adjusted Import Tariff* for the treatment counties is 0.794, rising to 4.113 in the post-trade war period. In contrast, in Panel B, the corresponding values for the control counties are from 0.225 to 0.763, respectively. These figures indicate that treatment counties experienced a substantially larger increase in EMP-adjusted import tariff level relative to control counties.

Import Exposure is the log difference between the *Post-TW EMP-Adjusted Import Tariff* relative to the *Pre-TW EMP-Adjusted Import Tariff*, which is defined in Equation 3.

Import Exposure is the critical measure that we use to construct our treatment and control groups. Table 1 shows that the mean (median) of *Import Exposure* in the treatment group is 1.007 (0.987) and the mean (median) of *Import Exposure* in the control group is 0.309 (0.341). That is, the treatment group has a larger *Import Exposure* on average.

We also report summary statistics on key household demographic characteristics, including age, income, household size, race, educational attainment, employment status, and marital status. While exposure to protective trade policies differs significantly between the treatment and control groups, their socio-economic profiles are broadly comparable. This similarity provides reassurance that our results are unlikely to be driven by confounding household-level omitted variables, and instead reflect the causal impact of protective trade policy exposure.

4 Identification Strategy

4.1 Identification Challenges

We confront three identification challenges in assessing the impact of protective trade policies on household consumption. First, tariffs are implemented at the product level as a uniform national policy, requiring us to exploit regional variation in tariff exposure to identify households that are differentially affected.

Second, the trade war escalated rapidly over a short period, yet most macroeconomic indicators—such as GDP—are only available at annual frequency or at more aggregated geographic levels, thereby limiting their usefulness in capturing the real-time, localized effects of the trade war.[9]

Third, the trade war may affect household consumption through multiple channels, com-

[9]For instance, the Bureau of Economic Analysis reports quarterly GDP at the state level and only annual estimates at the county level.

plicating the interpretation of observed declines in spending. On the supply side, higher tariffs can restrict product availability, increase retail prices, and shift the supply curve upward - leading to reduced consumption through the classic pass-through effects. On the demand side, retaliatory tariffs may dampen exports to China, adversely impacting local businesses, suppressing wage income, and weakening consumer demand. Similarly, U.S. import tariffs can generate negative income effects by disrupting upstream and downstream production within affected industries. To credibly isolate the demand-side effects of import tariffs - central to our analysis - we need to explicitly control for both price pass-through and retaliatory tariff exposure. Our aim is to demonstrate that, independent of the well-documented supply-side and retaliation effects, protective trade policies fail to shield the domestic labor market and, in fact, contribute to a decline in household welfare.

4.2 Identification Strategy

To address these challenges, we adopt a Difference-in-Differences (DiD) design and construct treatment and control groups based on cross-county variation in tariff exposure, following Waugh (2019). While tariff changes are uniform at the national level, counties differ in their industrial composition and employment shares, resulting in heterogeneous exposure. For example, if the Machinery industry is heavily tariffed, counties with a larger employment share in Machinery - presumably "protected" by the tariffs - experience greater exposure than counties where Machinery represents a smaller share of the workforce.

We rely on both $Import\ Exposure_c$ and $Export\ Exposure_c$, defined in Section 3.2.3 and calculated in Equation 3, to exploit the aforementioned variations. Specifically, we assign approximately 60,000 Nielsen households into a 5×5 matrix. We first sort households into quintiles based on $Export\ Exposure$, then further partition each quintile into five subgroups based on $Import\ Exposure$, yielding 25 groups in total.

Within each $Export\ Exposure$ quintile, households in counties with the lowest and highest *Import Exposure* form the control and treatment groups, respectively. This stratification allows us to isolate the effects of import exposure while holding export exposure relatively constant. The treatment group includes 11,562 households from 571 counties, and the control group comprises 12,363 households from 993 counties. Figure 5 presents the geographic distribution of households in both groups.

Our primary dependent variable is household quarterly spending. Figure 6 plots the average percentage change of quarterly spending relative to the pre-trade war mean for both groups. The pattern of raw data reveals comparable pre-trade war spending levels, with the treatment group exhibiting lower consumption growth relative to the control group post-trade war. Our sample period spans from 2017Q2 to 2019Q3. The first phase of the U.S.-China trade war began in July 2018, so our post period covers 2018Q3 to 2019Q3, while the before period spans 2017Q2 to 2018Q2. Both periods consist of five quarters. We exclude data after 2020 and do not test for longer-term effects for two main reasons: (1) U.S.-China negotiations began in late 2019, culminating in a formal truce in January 2020, and (2) more importantly, the COVID-19 pandemic, which emerged in early 2020, likely had significant effects on household consumption and thus contaminate the interpretation of our results.[10]

The main specification is:

$$Quarterly\ Spending_{i,t} = \beta_1 Treat \times Post + \beta_2 Treat + \beta_3 Post + FEs + \epsilon_{i,t} \tag{4}$$

Here, β_1 captures the DiD effect. Household and time fixed effects control for unobserved household heterogeneity and seasonality.

In addition to the standard DiD specification, we perform robustness checks using a continuous DiD framework that does not rely on predefined treatment and control groups.

[10]Focusing on a short window allows us to isolate the immediate response in consumption, avoiding the confounding effects of long-term changes such as shifts in imports or production relocation to other countries (Alfaro and Chor, 2023; Dang, Krishna, and Zhao, 2023; Freund et al., 2024; Fajgelbaum et al., 2024; Grossman, Helpman, and Redding, 2024).

Instead, we include all Nielsen households and proxy treatment intensity using the continuous measure $Import\ Exposure_c$, while explicitly controlling for $Export\ Exposure_c$. The empirical model is defined as below:

$$\begin{aligned} Quarterly\ Spending_{i,t} =& \beta_1 Import\ Exposure_c \times Post + \beta_2 Export\ Exposure_c \times Post \\ &+ \beta_3 Import\ Exposure_c + \beta_4 Export\ Exposure_c \\ &+ \beta_5 Post + FEs + \epsilon_{i,t} \end{aligned} \tag{5}$$

4.3 Demand-Side vs. Supply-Side Channels

The empirical strategy explained in Section 4.2 allows us to isolate the effects of retaliatory tariffs from those of protective import tariffs. A remaining empirical challenge, however, is determining whether the observed decline in consumption is driven by demand contraction or supply-side adjustments due to tariff pass-through. Higher import tariffs increase the prices of foreign goods by shifting the supply curve upward, leading to a reduction in equilibrium consumption—an effect observationally equivalent to a negative demand shock. If the decline in total spending were primarily due to supply-side factors, it would imply that our treatment group experienced a disproportionately larger supply contraction relative to the control group. Nevertheless, supply-side explanations are unlikely to account for our main results for three key reasons.

First, as illustrated in Figure 2, nearly 50% of consumption in the Nielsen Data comprises deli items, fresh produce, dry groceries, and dairy products—categories predominantly sourced domestically or locally. These goods are largely insulated from direct import tariff effects, limiting the scope for supply-driven price adjustments.

Second, we conduct product-level analysis to examine co-movements in prices and quantities, exploiting their distinct implications for demand versus supply shocks. While both a leftward demand shift and an upward supply shift reduce equilibrium quantities, they exert opposing effects on prices: demand contraction depresses prices, whereas supply contraction raises them. By tracking directional changes in product spending, quantities purchased, and unit prices, we assess whether demand- or supply-side forces dominate the observed adjustments.

Third, in Equation 6, we include both the Time × Product and the Household × Product fixed effects to compare consumption of identical goods across households within the same period. The former fully absorbs time-varying product-level dynamics. This strategy isolates demand-side responses from supply-driven price fluctuations attributable to tariff pass-through, ensuring that our estimates reflect shifts in household behavior rather than exogenous cost shocks.

$$\begin{aligned} Product\ Spending_{i,p,t}(Quantity_{i,p,t}, Price_{i,p,t}) = &\beta_1 Treat + \beta_2 Post + \\ &\beta_3 Treat \times Post + FEs + \epsilon_{i,p,t} \end{aligned} \tag{6}$$

5 Results

5.1 Baseline Regressions

Table 2 shows our baseline results. This table reports estimates from Difference-in-Differences regressions of household quarterly spending on the treatment indicator (*Treat*), the post-treatment period indicator (*Post*), and their interaction. Each observation corresponds to the total spending by household i in quarter t. The dependent variable in columns (1) and (2) is *Quarterly Spending*, defined as the total dollar value tracked by NielsenIQ. Columns (3) and (4) use *Ln*(*Spending*), columns (5) and (6) use the *Pct Change* in spending, and columns (7) and (8) use *YoY Growth*. The *Pct Change* variable uses the household's average quarterly spending in the pre-trade war period as the baseline, while *YoY Growth* is calculated relative to spending in the same quarter of the prior year. *Treat* is a binary variable equal to one if the household belongs to the treatment group. *Post* equals one for quarters from 2018Q3 to 2019Q3, and zero otherwise. The sample includes household-quarter observations from 2017Q2 through 2019Q3. Columns (1), (3), (5), and (7) include Household fixed effects. Columns (2), (4), (6), and (8) include both Household and Time (i.e., quarter) fixed effects, which absorb the variation in both $Treat$ and $Post$. By including the Time fixed effect, we control for unobservable factors that impact households in both the treatment and control groups at the same time, such as macro-level factors. Standard errors are clustered at the household level.

The results show that households in the treatment group spent less than the households in the control group due to the impact of import tariffs implemented on imports from China. The coefficient of $Treat \times Post$ in Column 1 suggests that the treatment group households spent \$14.21 less than the control group households each quarter due to the trade war, or about 1.06% of the sample mean of treatment group households' quarterly spending (\$1,344). In Columns 3, 5, and 7, the results also indicate that the treatment group households reduced consumption by 1.06% (Column 3), 1.19% (Column 5), or 1.54% (Column 7) more than the control group households due to the trade war. The negative impact on consumption is economically significant - to contextualize, the average annual change rate of the Personal Consumption Expenditures per capita between 2008 and 2017 is 2.34%[11]. In Columns 2, 4, 6 and 8, the specification including both Household and Time fixed effects yield quantitatively similar results. All the coefficients are significant at the 5% level or above.

We also carry out a dynamic analysis of the trade war impact. Instead of using the dummy variable $Post$ in Equation 4, we create 9 dummy variables indicating different quarters from 2017Q3 to 2019Q3, and we use 2017Q2 as the benchmark. We also create the interaction terms between these quarterly dummies and $Post$ and the new specification is reported as Equation 7. α_i is the Household fixed effects. The coefficients of these interaction terms, θs, show the relative difference between the treatment group and the control group, and are

[11]The number is calculated using the "Personal consumption expenditures per capita", Federal Reserve Bank of St. Louis.

plotted in Figure 7.

$$
\begin{aligned}
Pct\ Change_{i,t} = &\beta_1 Treat + \beta_{2017,Q3} \times Quarter_{2017,Q3} + ... + \beta_{2019,Q3} \times Quarter_{2017,Q3} + \\
&\theta_{2017,Q3} \times Treat \times Quarter_{2017,Q3} + ...\theta_{2019,Q3} \times Treat \times Quarter_{2019,Q3} \\
&+ \alpha_i + \epsilon_{i,t}
\end{aligned}
\tag{7}
$$

Figure 7 reveals two key findings. First, in the pre-treatment period prior to July 2018, the estimated coefficients fluctuate around zero and are statistically insignificant, indicating that consumption patterns between treatment and control groups followed parallel trends before the trade war. This supports the validity of our Difference-in-Differences design.

Second, the figure shows that the negative consumption effects of the trade war emerged predominantly in 2019, with limited impact during the initial phase of the conflict. This delayed response likely reflects both the gradual transmission mechanism of tariffs to consumer behavior and the escalating nature of the trade restrictions.The initial 25% tariffs, implemented in July and August 2018, affected only \$50 billion of Chinese imports, representing a mere 10% of the \$505 billion in total goods imported from China in 2017. The situation escalated in September 2018 when 10% tariffs were imposed on an additional \$200 billion of imports. However, the most substantial changes occurred in May 2019 when these tariffs were raised to 25% following failed trade negotiations, followed by another round of 10% tariffs on \$300 billion of additional imports in August 2019. This chronology explains why the adverse effects on consumption became most pronounced in 2019.

5.2 Robustness Checks on the Baseline Results

In the DiD analysis above, we find that households in the treatment group - those facing larger increases in protective tariff exposure - exhibit significantly lower consumption levels relative to the control group following the onset of the trade war. This result implies that import tariffs may fail to deliver their intended protective effect and instead erode local consumption capacity.

To assess the robustness of our baseline findings, we perform two robustness analyses: (1) a continuous DiD regression and (2) a panel regression. In these new specifications, we extend the analysis to include all households from the Nielsen data, controlling for retaliatory tariff-related measures to isolate their effect. These tests evaluate the sensitivity of our results to alternative definitions of treatment and control groups, while also assessing the external validity of our conclusions across the entire Nielsen household sample.

In the first robustness check, we expand the sample to include all households and measure treatment intensity using a continuous variable - household-level import exposure. To fully account for the effects of retaliatory tariffs, we also control for the export exposure faced by the household. The regression follows the specification in Equation 5, with results reported in Table 3. As shown in the table, the interaction terms are statistically significant at the 1% level across all eight specifications. The economic magnitude is also meaningful: a one-standard-deviation increase in $Import\ Exposure$ (0.333) corresponds to an \$8.06 (0.333 $\times$ 24.2095) decline in post-trade-war consumption, representing approximately a 0.6% contraction from the sample mean (\$1,331). These findings, consistent with our baseline results, further reinforce the conclusion that import tariffs adversely affect household consumption.

In our second robustness test, we estimate a panel regression using the full set of household-quarter observations. Instead of relying on a binary $Post$ indicator to capture the abrupt shift in trade war exposure, we incorporate time-varying, employment-adjusted (EMP-adjusted) import and export tariff levels, as defined in Equation 2. This approach enables us to capture the dynamic effects of the time-varying tariff changes throughout the course of the trade war.

The results, presented in Panel A of Appendix Table A.2, demonstrate that the coefficients on EMP-adjusted import tariffs are statistically significant at the 1% level across all eight specifications. Consistent with our baseline findings, these estimates indicate that higher EMP-adjusted import tariffs exert a significant negative effect on household consumption.

5.3 Disentangling the Demand and Supply Effects

The observed consumption decline during the trade war could stem from either a downward shift in the demand curve, an upward shift in the supply curve, or some combination of both. We aim to disentangle the demand-side channel from the well-documented supply-side channel, by analyzing not only the total consumption but also the joint dynamics of quantities and prices.

We construct a panel dataset representing household i's consumption on product p in quarter t, including total spending, the quantity purchased, and the average unit price ($Product\ Spending_{i,p,t}$, $Product\ Quantity_{i,p,t}$, $Product\ Price_{i,p,t}$, respectively). If a household does not spend any money on a product in that quarter, both $Product\ Spending_{i,p,t}$ and $Product\ Quantity_{i,p,t}$ are set to zero. It's important to note that the product may still be on the shelf; the household simply did not consume any of it during that quarter. Therefore, if $Product\ Spending_{i,p,t}$ and $Product\ Quantity_{i,p,t}$ are zero, we use the average price paid by other households in that county for the quarter as $Product\ Price_{i,p,t}$. As a robustness check, we also report regression results on a dataset excluding observations with zero consumption. The specification is in Equation 6.

Table 4 reports the regression results. In Columns 2, 4, and 6, we include Household $\times$ Product fixed effect and Time $\times$ Product fixed effect, which fully absorb the variations of the $Treat$ and $Post$ and control for any time-varying unobservable product-level dynamics. Panel A shows the results on the panel dataset including zero consumptions. The coefficients of Column 2 suggest that: relative to the control group, the spending of the treatment group on the same product is lower by \$0.0080 after the outbreak of the trade war, which is 0.77% of the sample mean (\$1.045). The quantity is lower by 0.0024, which is 0.8% of the sample mean (0.300). The price is lower by \$0.0062, which is 0.174% of the sample mean (\$3.557). Panel B shows the results on the panel data excluding zero consumptions. The results in Column 2 suggest that: Relative to the control group, the product spending of the treatment group is lower by \$0.0411 after the outbreak of the trade war, which is 0.65% of the sample mean (\$6.330). The quantity is lower by 0.0084, which is 0.46% of the sample mean (1.814). The price is lower by \$0.0055, which is 0.14% of the sample mean (\$3.858). We include the Household fixed effect instead of the Household × Product in Columns 1, 3, and 5; the results are quantitatively similar.

The results indicate reductions in total spending, quantity purchased, and prices at the product level. These patterns are less consistent with a supply-side explanation, as an upward shift in the supply curve would typically result in higher prices rather than lower ones. While some supply contraction may occur, the observed price declines suggest that demand contraction plays a significant role in reducing consumption during the trade war. Households in the treatment group exhibit lower retail prices post-trade-war compared to the control group, further supporting demand-side forces as the primary driver of reduced spending.

5.4 Robustness Checks on the Supply v.s. Demand Analysis

We perform two robustness checks on the product-level regression results presented in Section 5.3. As in Section 5.2, we extend the analysis to include all households in the Nielsen data, beyond the treatment and control group samples, and conduct two additional tests: (1) a continuous Difference-in-Differences regression, and (2) a panel regression.

In the first robustness check, we expand the product-level consumption data to include all households, using two continuous variables—household-level import exposure and export exposure—to measure treatment intensity. As in Section 5.3, we control for Household (or Household × Product) and Time × Product fixed effects, and conduct the analysis on two distinct samples: one that includes zero consumption observations and another that excludes them. The results are reported in Table 5. Panel A presents the results for the sample including zero consumption observations, where the coefficients on the interaction term *Import Exposure* × *Post* are negative and statistically significant at the 5% level or higher across all six specifications. Panel B of Table 5 reports the results for the sample excluding zero consumption observations. The negative coefficients of *Import Exposure* × *Post* in both panels suggest that households more exposed to the increase in import tariffs following the trade war spend less, purchase fewer quantities, and pay lower prices. These findings are consistent with the patterns observed in Table 4.

In the second robustness check, we estimate a panel regression incorporating household-product-quarter observations across all U.S. counties. We employ time-varying, employment-adjusted (EMP-adjusted) import and export tariff levels as explanatory variables, following the approach in Panel A of Appendix Table A.2. We control for the same Household (or Household × Product) and Time × Product fixed effects. The results are presented in Panel B and Panel C of Appendix Table A.2. Panel B reports results from the sample including zero-consumption observations, while Panel C reports results from the sample excluding zero-consumption observations. In all specifications, the coefficients on import tariffs are negative, indicating that households in counties facing higher Chinese import tariffs reduce spending, quantity purchased, and, crucially, pay a lower price at the product level.

Results from these robustness tests reaffirm the findings in Table 4, specifically that prices decline in the treatment group relative to the control group. These results further substantiate our previous conclusion that the negative impact of increased import tariffs is primarily driven by reduced demand, rather than supply constraints, which would have been expected to result in a relative increase in prices.

5.5 Cross-Sectional Analysis

5.5.1 Household Social-Economic Profiles

In Table 6, we investigate whether the impact of the trade war on consumption varies across households with different demographic and economic characteristics. Sub-sample analyses are conducted based on household income (Panel A) and age (Panel B), utilizing information from Nielsen. The dependent variable is the *Pct Change*, representing quarterly spending scaled by the household's pre-trade war average spending, and the specification follows our baseline model in Equation 4.

In Panel A, households are categorized by income: those earning less than 30K, between 30K and 100K, and above 100K annually. In all income brackets, treatment groups experienced a reduction in consumption relative to the control groups after the trade war, although the reduction is not statistically significant in the lowest income group (income less than 30K). The magnitude of the reduction is smaller for the lowest income group, with a coefficient of -0.223% (Column 2), which is less than that for the middle-income group (-1.201%, Column 4) and upper-middle-income group (-1.995%, Column 6). Note that due to sample limitations - specifically, very few households earning more than 200K agreed to be surveyed by Nielson. Thus the above 100k group mainly consist of households earning between 100k and 200k, which we interpret as the upper-middle-income segment.

In Panel B, households are categorized into three age groups: less than or equal to 35 years old, 35 to 60 years old, and above 60 years old. A household is classified into an age group if the average age of household head(s) falls into that age bracket. The coefficients are negative across all groups, although the results for the younger and older age groups are statistically insignificant.

Overall, our findings suggest that middle- and upper-middle-income households, as well as middle-aged households, bear a greater burden from the trade war. This may indicate that younger workers, earning entry-level salaries, are less affected by the increase in import tariffs. Similarly, households with senior adults above 60, who are likely retired, appear less affected, as they depend on retirement income rather than wage-based earnings.

5.5.2 Types of Household Consumption

In this section, we examine how household consumption responses vary across different product categories. Following the NielsenIQ classification, products are grouped into ten major product departments. We further aggregate these departments into three mutually-exclusive and interpretable consumption types: durables, discretionary goods, and necessities. The durable category includes 1) General Goods, such as appliances, cookware, and automotive products. Discretionary goods consist of 2) Health and Beauty Products, 3) Dry Groceries (e.g., candy and snacks), 4) Alcoholic Beverages, and 5) Non-Food Groceries (e.g., air fresheners and deodorizers). Necessities encompass 6) Frozen Foods, 7) Dairy, 8) Deli, 9) Meat, and 10) Fresh Produce (e.g., vegetables).

In the next step, we construct a balanced panel at the household–department group–quarter level, where each observation summarizes a household's total spending on products that belong to a specific department group in a given quarter. If no purchases are recorded for a particular department group in a given quarter, spending is set to zero. We regress total department-level spending on $Treat$, $Post$, and consumption type dummies using a triple Difference-in-Differences framework. The sample covers quarterly observations from 2017Q2 to 2019Q3. The variable $Post$ is a dummy equal to one for quarters t between 2018Q3 and 2019Q3, and zero for quarters on or before 2018Q2. We include Household $\times$ Department Group and Time $\times$ Department Group fixed effects. Note that the main effects of both $Treat$ and $Post$ are fully absorbed by the fixed effects.

Regression results are presented in Table 7. Columns (1) to (3) introduce the $Durable$, $Discretionary$, and $Necessity$ dummies, respectively, while column (4) includes all three.

The coefficients on $Necessity$ and its corresponding triple interaction terms are omitted and serve as the baseline in column (4). The estimates reveal significant heterogeneity in the consumption response across consumption types. The coefficient on $Treat \times Post \times Discretionary$ is negative and statistically significant at the 5% level in both columns (2) and (4), indicating that discretionary spending declines more sharply. In contrast, the coefficient on $Treat \times Post \times Necessity$ is positive and statistically significant, and its magnitude largely offsets the effect of $Treat \times Post$. The coefficient on $Treat \times Post \times Durable$ is negative, suggesting a larger contraction than the average treatment effect, though it is not statistically significant in columns (1) and (4). These findings are consistent with the view that discretionary goods exhibit greater consumption elasticity in response to adverse income shocks.

6 Mechanism of the Consumption Response

6.1 The Labor Market and Income Shock

Our analysis thus far suggests that the trade war has a negative impact on consumption, primarily driven by a contraction in demand. To further explore the mechanisms underlying this demand contraction, we examine the trade war's effects on the labor market. Specifically, we hypothesize that the trade war leads to a reduction in wages, thereby constraining household consumption.

We construct a quarterly county-level wage measure using data from the Bureau of Labor Statistics (BLS), which provides the average weekly wage and total employment by NAICS industry for every county, quarter by quarter. The county-level wage is calculated as an employment-weighted average of weekly wages across all private industries within a county. To capture wage dynamics, we consider three additional dependent variables: the logarithm of wages, the percentage change relative to the pre-trade war average, and the year-on-year growth rate of county-level wages. We also aggregate employment across all industries within a county to measure total employment.

In Table 8, we present the Difference-in-Differences estimates for wages and employment. Treatment group counties exhibit weekly wage that are \$10.27 lower (Column 4) than those in control group counties, representing approximately 1.4% of the sample mean (\$746). The regression results in Column 6, where the logarithm of weekly wages is used as the dependent variable, indicate that wages in treatment group counties are 1.87% lower post-trade war. When measured as the relative change to the pre-trade war average, weekly wages in treatment counties are 1.13% lower (Column 8). Similarly, the year-on-year growth rate of weekly wages in treatment counties is 1.96% lower (Column 10) compared to control group counties following the trade war. The trade war also reduces aggregate employment in treatment group counties by 0.26% (Column 2) relative to control group counties, although this difference is not statistically significant. This finding aligns with the slower adjustment of employment relative to wages, reflecting the labor market's inherent stickiness. We include either County fixed effects or both County and Time fixed effects, and the results remain quantitatively similar. Overall, these findings provide support for our hypothesis that the trade war negatively impacts the labor market by reducing wages, which in turn constrains household consumption.

We further investigate the trade war's impact on labor markets separately across the tradable and non-tradable sectors in Table 9. Given that the tradable sector is more directly exposed to international trade than the non-tradable sector (Autor, Dorn, and Hanson, 2013), we expect differential effects. For each county, we calculate employment and wages separately for the tradable and non-tradable sectors.

In Columns (1), (3), (5), (7), and (9) of Table 9, we control for County and Time fixed effects. In Columns (2), (4), (6), (8), and (10), we include County $\times$ Time fixed effects to compare wage and employment outcomes between the tradable and non-tradable sectors within the same county. The models with County × Time fixed effects reveal that, relative to the non-tradable sector, the tradable sector loses 9.03% more jobs (Column 2). Wages in the tradable sector are \$11.29 lower (Column 4) post-trade war, and the *Wage Pct Change* is -0.22% slower (Column 8), although the result is statistically insignificant. When measured as the Year-on-Year growth rate, tradable sector wages grow 2.15% slower (Column 10) than those in the non-tradable sector. These results demonstrate that the tradable sector, which is directly exposed to the trade war, experiences larger declines in both employment and wages.

6.2 (Vertical) Distribution of Tariffs within Targeted Industries

Finally, we explain why protective tariffs harm income, employment, and consumption for households residing and working in areas where local industries are highly overlapped with Chinese imports. Notably, building on the trade data observed in the 1990s and early 2000s, prior research on the "China Shock" illustrates that import competition from China negatively impacts the U.S. labor market and workers' welfare (Autor, Dorn, and Hanson, 2013). Building on this literature, one might expect that reversing the integration of China and global trade could mitigate these adverse effects.

However, our empirical findings suggest the opposite outcome, which we attribute to the evolving roles of Chinese and U.S. firms within the global trade system. In the early 2000s, Chinese firms primarily competed horizontally with lower-end U.S. firms within the same industries. By 2018, however, Chinese and U.S. firms had become vertically integrated, occupying complementary positions along the intra-industry value chain. As Wang et al. (2018) and Aghion et al. (2024) argue, this shift reflects the intertwined nature of U.S. and Chinese industries, and suggests that reverting trade integration would harm local industries, the labor market, and households, rather than providing a net benefit.

For example, many U.S. firms outsourced production to China under Original Equipment

Manufacturer (OEM) or Original Design Manufacturer (ODM) models, retaining control over design and branding. This is especially prevalent in the consumer electronics and furniture sectors, which experienced the second and third largest tariff increases during the trade war. As another example, the pharmaceutical industry relies on key starting materials and Active Pharmaceutical Ingredients (APIs) imported from China. As a result, protective tariffs raise costs for firms that have offshored production and those that rely on Chinese intra-industry inputs[12].

The macro-level trade statistics exhibit a similar pattern, consistent with the examples provided above. Figure A.2 illustrates this evolution using data from UN Comtrade. The top panel shows the composition of U.S. imports from China by product category. The share of consumption goods has declined, while the shares of capital and intermediate goods have increased. In 2001, 53.2% of U.S. imports from China were consumption goods, 22.5% were capital goods, and 23.0% were intermediate goods. By 2017, these shares had shifted to 31.8%, 38.8%, and 27.5%, respectively, reflecting a substantial increase in capital and intermediate goods. The bottom panel of Figure A.2 presents China's market share in U.S. imports by category. In 2001, China accounted for 26% of U.S. consumption goods imports, peaking at 37% in 2010 before declining. In contrast, China's share of U.S. capital goods imports grew from 10.0% in 2001 to 39.4% in 2017, while its share of intermediate goods imports increased from 4.6% to 14.1%. These trends underscore the growing reliance of U.S. firms on Chinese supply chains. Imports from China are no longer limited to competing products or substitutes; rather, the rising share of capital and intermediate goods reflects the deepening interdependence of U.S. and Chinese industries. As such, tariffs on these imports impose higher costs on U.S. firms that depend on Chinese inputs.

We hypothesize that there are significant heterogeneous effects across industries that align with the supply chain perspective outlined above. In our empirical analysis, we employ

[12] Tariffs may also propagate through supply networks, affecting both downstream and upstream industries. These effects extend beyond manufacturing sectors. For instance, tariffs on computers and printers may increase office work costs (Wang et al., 2018).

a product-level classification to assess whether local firms are more vertically integrated with Chinese firms within the same industry or are more likely to compete directly with imports from China. To achieve this, we categorize imported goods into three groups: capital goods, intermediate goods, and consumption goods. Using the Harmonized System (HS) code for each imported good, we map it to its corresponding Broad Economic Category (BEC). We then link each BEC to its end-use classification in the System of National Accounts (SNA), enabling us to classify each imported good into one of the three categories: capital goods, intermediate goods, or consumption goods.

In Figure A.3, we present the distribution of imposed tariffs within each targeted industry, illustrating the percentage increase in tariffs for capital goods, intermediate goods, consumption goods, and unclassified goods, respectively. The figure highlights that even industries with similar overall protective tariff increases can exhibit substantial variation in the distribution of those increases. For instance, although the Plastics, Fishing, and Compute&Electronics industries all experienced a 10% increase in tariffs during the trade war, the underlying drivers of these increases differ markedly. In the Fishing sector, the tariff increase is primarily driven by higher tariffs on consumption goods. In contrast, the increase in the Plastics sector is largely attributable to tariffs on intermediate goods, while in the Compute&Electronics sector, the increase is predominantly driven by tariffs on capital goods.

Exploiting the heterogeneous distribution of tariffs within the targeted industry, we hypothesize that import tariffs on capital and intermediate goods are more likely to adversely impact local production, thereby inducing a stronger contraction in household spending. In contrast, tariffs on final consumption goods are expected to impose relatively smaller economic costs. This prediction is based on the premise that U.S. firms, on average, occupy positions closer to the consumption end of the value chain within their respective industries.

Specifically, we first calculate county-level tariffs for the three categories - capital goods, intermediate goods, and consumption goods - using the methodology outlined in Equation 2 and Equation 3. We then define treatment counties using a similar approach and create three dummy variables: $Capital$, $Intermediate$, and $Consumption$. $Capital$ equals one if a county's increase in capital goods tariffs exceeds the median increase across all sample counties. Similarly, $Intermediate$ and $Consumption$ are defined based on intermediate goods and consumption goods tariffs, respectively. These dummy variables capture whether a county's tariff increase during the trade war is primarily driven by tariffs on capital goods, intermediate goods, or consumption goods. As noted earlier, we hypothesize that tariff increases on capital and intermediate goods are more likely to harm local firms by raising costs, while tariff increases on consumption goods are more likely to reduce competition from Chinese imports.

In Table 10, we present the results on the triple Difference-in-Differences regressions of household consumption on the $Treat$, $Post$, and the distribution of tariff proxies. Columns (1) and (2) report results with the interaction term $Treat \times Post \times Capital$, columns (3) and (4) with $Treat \times Post \times Intermediate$, and columns (5) and (6) with $Treat \times Post \times Consumption$. The coefficients on $Treat \times Post \times Capital$ and $Treat \times Post \times Intermediate$ are negative but statistically insignificant, indicating that counties with large increases in tariffs on capital or intermediate goods exhibit a reduction in consumption similar to the average treatment effect.

In contrast, the coefficients on $Treat \times Post \times Consumption$ in Columns (5) and (6) are significantly positive, indicating that households in counties experiencing tariff increases on consumption goods are relatively better off compared to the average treatment group. However, when combined with the negative coefficient of $Treat \times Post$, the net effect remains negative. Columns (7) and (8), which include all three interaction terms ($Capital$, $Intermediate$, and $Consumption$) alongside $Treat \times Post$, yield qualitatively similar results. These findings reinforce the conclusion that our main results are primarily driven by counties where local firms are exposed to intra-industry tariff increases on capital and intermediate goods.

In conclusion, our results indicate that the reduction in consumption resulting from the trade war is primarily driven by tariff-induced increases in input costs. These negative cost shocks to firms are transmitted to the labor market, and the subsequent wage adjustments ultimately impact consumer spending. While protective import tariffs may provide some shelter for certain local industries, their positive effect on consumption is, at best, modest. This finding is consistent with Wang et al. (2018), Flaaen and Pierce (2024), Aghion et al. (2024) and Handley, Kamal, and Monarch (2025), who argue that U.S.-China trade relations are characterized more by supply-chain complementarity than by direct competition. As a result, tariffs have limited success in stimulating local production to substitute imports and pose significant risks of supply-chain disruption that bear substantial welfare loss.

7 Conclusion

This paper examines the household-level consequences of U.S. import tariffs on Chinese goods, implemented with the stated objective of protecting domestic industries. Using detailed consumption, employment, and trade data, we document three key findings: First, households in counties most exposed to protective tariff increases experience significant declines in aggregate consumption. Second, product-level analysis reveals that this reduction stems primarily from demand contraction, evidenced by simultaneous decreases in quantities purchased and prices. Third, these same counties exhibit relative wage declines, suggesting broader labor market effects.

Our results challenge the conventional wisdom underlying protective trade policy. Rather than strengthening local industries, the tariffs appear to have generated net negative effects through supply chain disruptions that outweigh any potential benefits to protected firms. The observed consumption and wage patterns are consistent with a scenario where input cost increases and production inefficiencies propagate through local economies.

These findings contribute to the household finance, political finance, and international trade literature by demonstrating how protective tariffs can generate unintended consequences at the household level. The results suggest that policymakers should consider both the direct protective effects and the general equilibrium consequences of trade barriers, particularly their potential to disrupt established supply chains and reduce household purchasing power.

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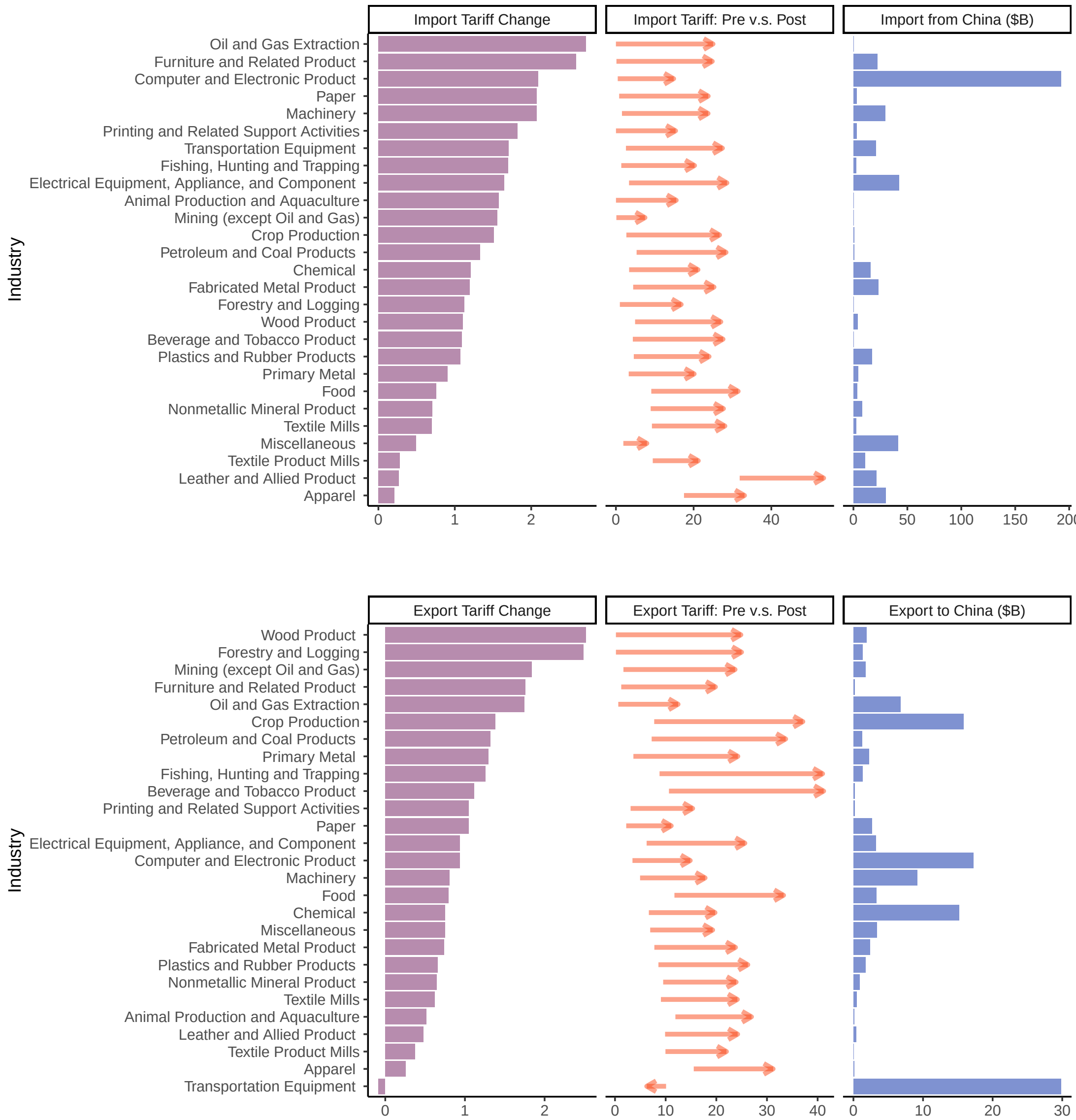
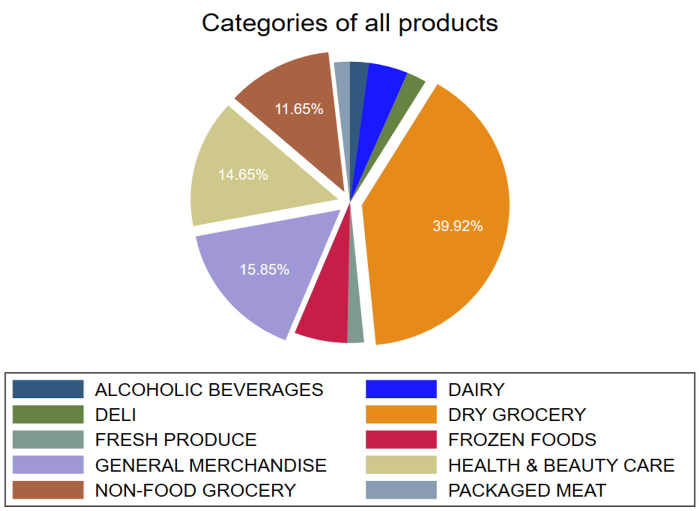
Figure 1. Changes in Tariff Rates, by Industry



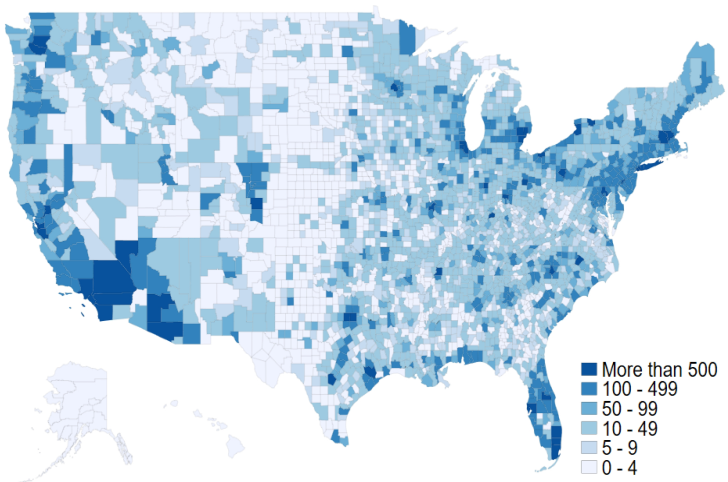
This figure presents industry-level breakdowns of: (1) tariff changes as defined in Equation 1 (Column 1); (2) pre- and post-trade war tariff rates (in percent, Column 2); and (3) total import and export values (in billions of U.S. dollars, Column 3). The top panel reports data for U.S. imports from China, while the bottom panel reports data for U.S. exports to China. Industries are ordered by the change in tariff rates between the pre- and post-trade war periods (Column 1).

Figure 2. Categories of Household Consumption



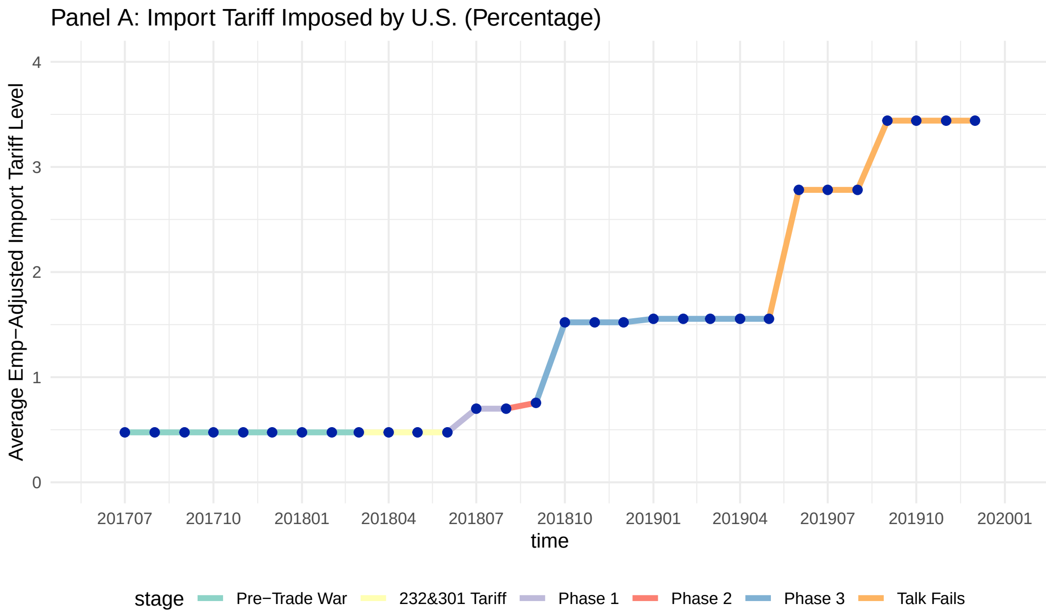
This figure presents the percentages of product purchases by their corresponding product categories.

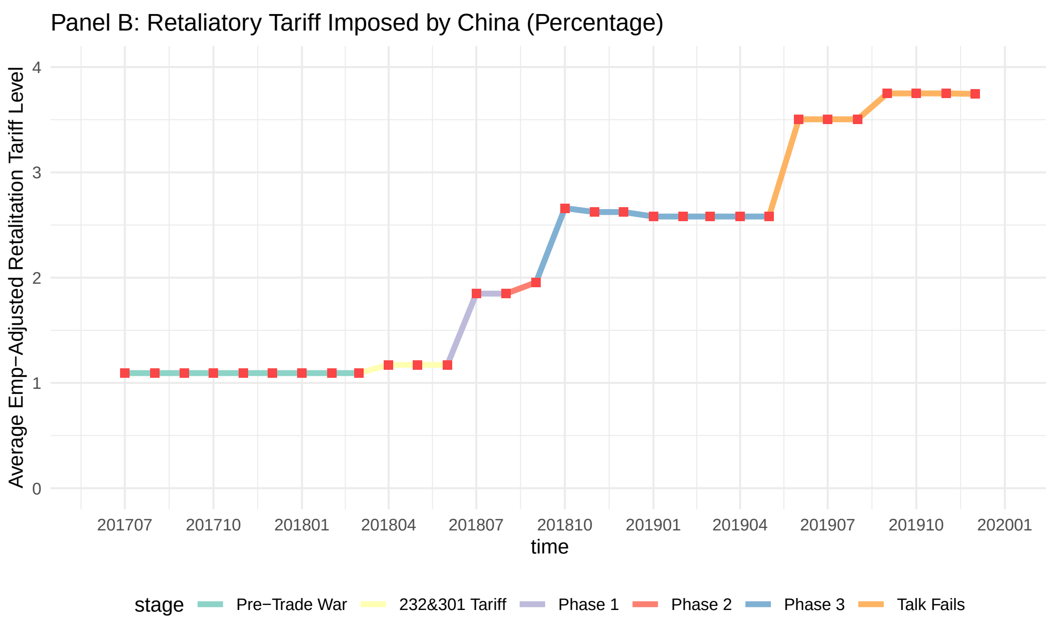
Figure 3. Geographic Distribution of the Surveyed Households in Nielsen



The figure plots the distribution of the surveyed households by location. Areas of the heat map filled with darker blue are populated with higher number of surveyed households.

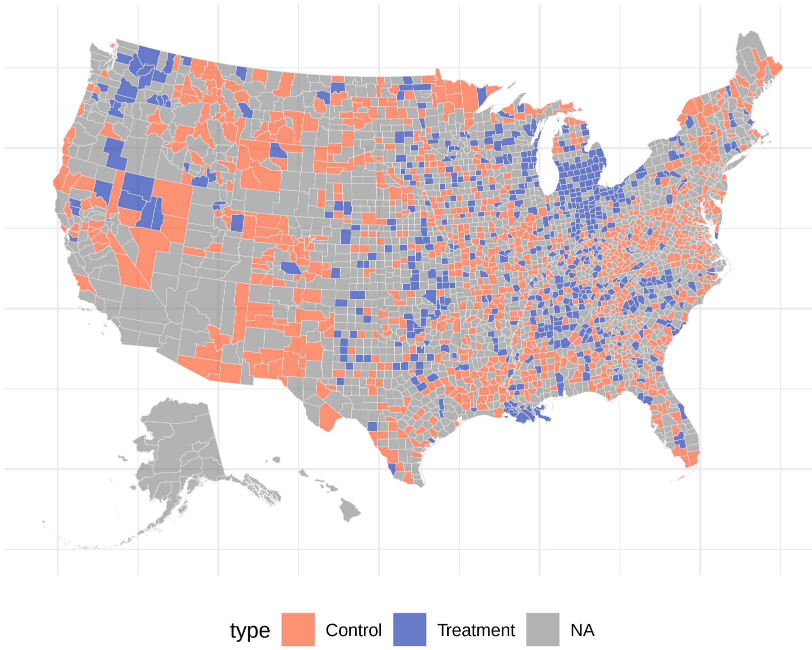
Figure 4. Timeline of the United States - China Trade War





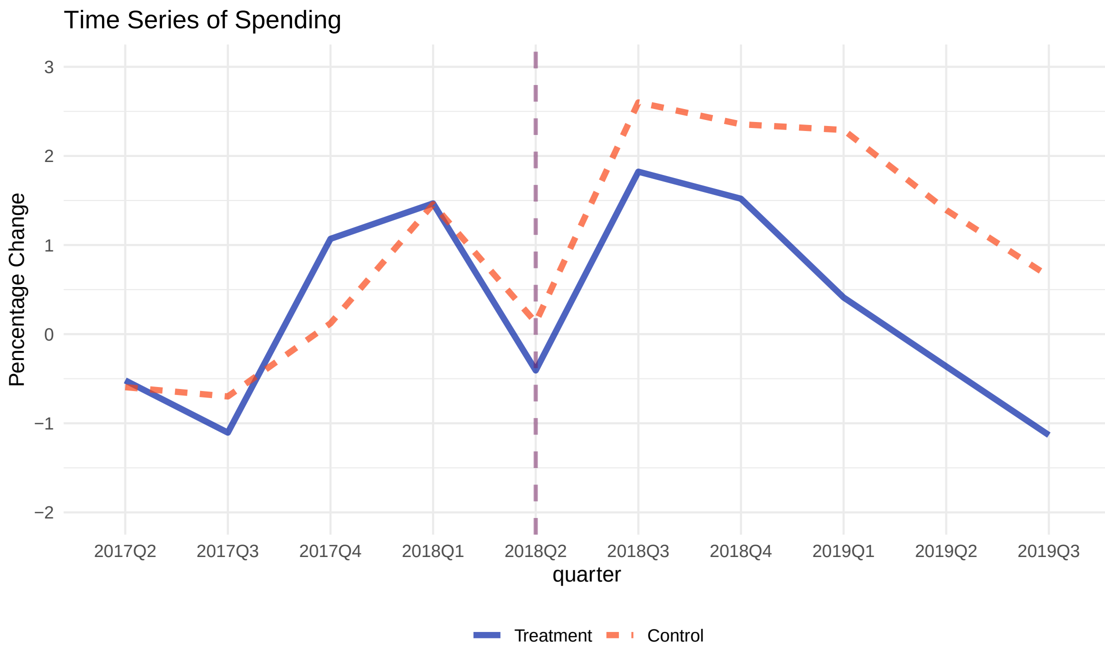
The figures plot the time-series of average EMP-adjusted import and retaliatory (export) tariff levels across U.S. counties. We first calculate the EMP-adjusted tariff level at the county level, and then plot the average of all counties on the vertical axis. Panel A presents the average EMP-adjusted import tariff on goods imported from China. Panel B displays the average EMP-adjusted retaliatory tariff on U.S. exports to China. Distinct phases of the trade war are demarcated using different color schemes to highlight variation in tariff exposure across time.

Figure 5. Geographic Distribution of Treatment and Control Counties



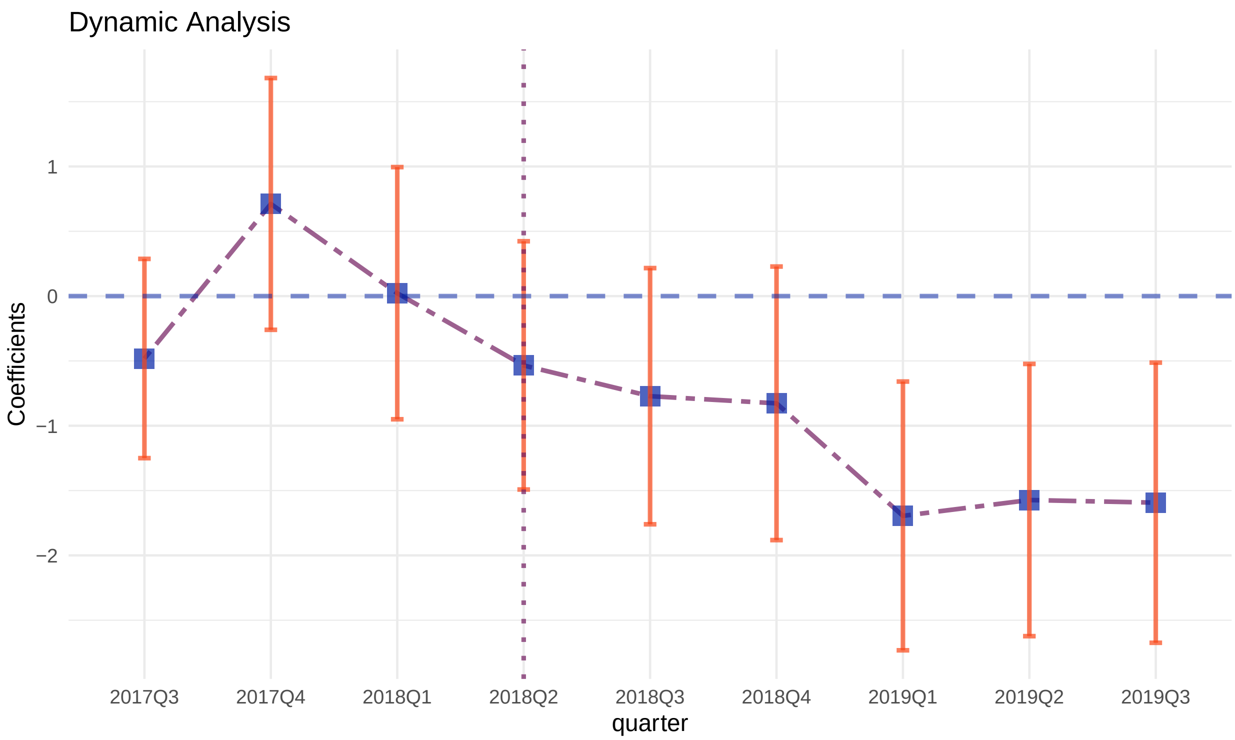
The figure visualizes the distribution of the treatment and control counties across the United States. The treatment group, highlighted in blue, consists of 571 counties and 11,562 households; while the control group, highlighted in orange, consists of 993 counties and 12,363 households.

Figure 6. Time-series Changes in Household Spending



This figure displays the time-series evolution of average quarterly household spending from Q3 2017 to Q3 2019. The blue line represents the mean spending of households in the treatment group, while the orange line reflects that of the control group. The vertical axis denotes the percentage change in average spending relative to the pre–trade war baseline.

Figure 7. Dynamic Analysis



This figure plots the coefficient estimates and the corresponding 10% confidence intervals for the interaction terms from the Difference-in-Differences specification described in Equation 7. These estimates capture the differential effects of import tariff exposure across treatment and control groups over time.

Table 1. Summary Statistics

This table presents summary statistics for the key variables used in the analysis. *Quarterly Spending* is measured at the household-quarter level, *Post-TW Emp-Adjusted Import Tariff*, *Pre-TW Emp-Adjusted Import Tariff*, and *Import Exposure* are measured at the county level, while all other variables are measured at the household level. For each variable, the number of observations, mean, median, minimum, maximum, and standard deviation are reported. Panel A summarizes statistics for the treatment group, and Panel B for the control group. Detailed variable definitions are provided in Appendix Table A.1.

Panel A: Treatment Group

	N	mean	p50	min	max	SD
Quarterly Spending($)	103,320	1,344	1,171	149.7	4,216	813.1
Post-TW Emp-Adjusted Import Tariff	571	4.113	3.666	0.701	15.75	2.099
Pre-TW Emp-Adjusted Import Tariff	571	0.794	0.683	0	3.524	0.520
Import Exposure	571	1.007	0.987	0.531	2.294	0.215
HouseholdSize	11,562	2.514	2	1	9	1.346
Age(<=35)	11,562	0.080	0	0	1	0.272
Age(35-60)	11,562	0.564	1	0	1	0.496
Age(>60)	11,562	0.355	0	0	1	0.479
College	11,562	0.166	0	0	1	0.372
Unemployed	11,562	0.248	0	0	1	0.432
Income(<30K)	11,562	0.190	0	0	1	0.392
Income(30K-100K)	11,562	0.640	1	0	1	0.480
Income(>100K)	11,562	0.170	0	0	1	0.376
Race(White)	11,562	0.841	1	0	1	0.365
Race(African)	11,562	0.098	0	0	1	0.298
Race(Asian)	11,562	0.024	0	0	1	0.154
Married	11,562	0.670	1	0	1	0.470

Panel B: Control Group

	N	mean	p50	min	max	SD
Quarterly Spending($)	110,296	1,341	1,171	149.7	4,216	812.7
Post-TW Emp-Adjusted Import Tariff	993	0.763	0.587	0	6.512	0.815
Pre-TW Emp-Adjusted Import Tariff	993	0.225	0.119	0	4.042	0.353
Import Exposure	993	0.309	0.341	0	0.648	0.209
HouseholdSize	12,363	2.429	2	1	9	1.327
Age(<=35)	12,363	0.081	0	0	1	0.274
Age(35-60)	12,363	0.535	1	0	1	0.499
Age(>60)	12,363	0.384	0	0	1	0.486
College	12,363	0.166	0	0	1	0.372
Unemployed	12,363	0.279	0	0	1	0.449
Income(<30K)	12,363	0.207	0	0	1	0.405
Income(30K-100K)	12,363	0.606	1	0	1	0.489
Income(>100K)	12,363	0.187	0	0	1	0.390
Race(White)	12,363	0.808	1	0	1	0.394
Race(African)	12,363	0.103	0	0	1	0.304
Race(Asian)	12,363	0.035	0	0	1	0.183
Married	12,363	0.643	1	0	1	0.479

Table 2. Baseline Regression

This table reports estimates from Difference-in-Differences regressions of household quarterly spending on the treatment indicator (*Treat*), the post-treatment period indicator (*Post*), and their interaction. Each observation corresponds to the total spending by household i in quarter t. The dependent variable in columns (1) and (2) is *Quarterly Spending*, defined as the total dollar value tracked by NielsenIQ. Columns (3) and (4) use *Ln*(*Spending*), columns (5) and (6) use the *Pct Change* in spending, and columns (7) and (8) use *YoY Growth*. *Treat* is a binary variable equal to one if the household belongs to the treatment group. *Post* equals one for quarters from 2018Q3 to 2019Q3, and zero otherwise. The sample includes household-quarter observations from 2017Q2 through 2019Q3. The *Pct Change* variable uses the household's average quarterly spending in the pre-trade war period as the baseline, while *YoY Growth* is calculated relative to spending in the same quarter of the prior year. Columns (1), (3), (5), and (7) include household fixed effects. Columns (2), (4), (6), and (8) include both Household and Time(Quarter) fixed effects, which absorb the variation in both *Treat* and *Post*. Standard errors are clustered at the household level and reported in parentheses. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively. Detailed variable definitions are provided in Appendix Table A.1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Quarterly Spending		Ln (Spending)		Pct Change		YoY Growth	
Treat×Post	-14.2135***	-14.0845***	-0.0106***	-0.0106***	-1.1856***	-1.1798***	-1.5393**	-1.5234**
	(-2.92)	(-2.89)	(-2.60)	(-2.58)	(-3.31)	(-3.28)	(-2.54)	(-2.51)
Post	-23.1388***		-0.0201***		0.7024***		-4.4355***	
	(-6.74)		(-6.96)		(2.76)		(-10.28)	
Observations	213,616	213,616	213,616	213,616	213,616	213,616	187,445	187,445
Adjusted R-squared	0.778	0.778	0.731	0.732	0.132	0.133	0.103	0.108
Household FE	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	N	Y	N	Y	N	Y	N	Y

Table 3. Robustness Check of the Baseline Regression

This table presents robustness checks for the baseline analysis in Table 2 , using a continuous Difference-in-Differences specification and an expanded sample. We expand the sample to include all households and counties available in the Nielsen data and incorporate both import and export tariff exposures at the household level. The sample consists of quarterly observations from 2017Q2 to 2019Q3. *Import Exposure* and *Export Exposure* are defined as in Equation 3. The regressions include the same set of fixed effects and dependent variables as in Table 2. Standard errors are clustered at the household level and reported in parentheses. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively. Detailed variable definitions are provided in Appendix Table A.1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Quarterly Spending		Ln (Spending)		Pct Change		YoY Growth	
Import Exposure×Post	-24.2095***	-24.4197***	-0.0173***	-0.0174***	-1.9310***	-1.9443***	-2.5088***	-2.5168***
	(-3.19)	(-3.21)	(-2.83)	(-2.85)	(-3.50)	(-3.52)	(-2.66)	(-2.67)
Export Exposure×Post	2.9158	3.4384	-0.0009	-0.0006	0.0298	0.0582	0.4688	0.4877
	(0.27)	(0.32)	(-0.11)	(-0.07)	(0.04)	(0.08)	(0.36)	(0.37)
Post	-24.5687***		-0.0275***		0.5680*		-3.4715***	
	(-5.48)		(-7.56)		(1.72)		(-6.19)	
Observations	596,427	596,427	596,427	596,427	569,803	569,803	494,912	494,912
Adjusted R-squared	0.794	0.795	0.769	0.770	0.135	0.137	0.109	0.113
Household FE	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	N	Y	N	Y	N	Y	N	Y

Table 4. Decomposing the Demand and Supply Effects

In this table, we regress the spending, quantity, and unit price sold for the products purchased by both the treatment and control households in a Difference-in-Differences setting. Please note that the level of observation in this analysis is Household - Product - Quarter, which is different from that in Table 2. The analysis utilizes a panel dataset, where each data point represents the total spending, total quantity, and average price of a specific product (p) purchased by a household (i) during a particular quarter (t). *Treat* is a dummy variable that turns on when the household is in the treatment group. We only include the quarterly observations from 2017Q2 to 2019Q3. The *Post* is a dummy variable that equals one for every quarter t that falls between 2018Q3 and 2019Q3, and equals zero for every quarter t observed on or before 2018Q2. In column 1, 3 and 5, we include the household and Time × Product FEs. In column 2, 4 and 6, we include both the Household × Product and Time × Product fixed effects. The variations in both *Treat* and *Post* are fully absorbed by the fixed effects. The dependent variables are *Product Spending* (columns 1 and 2), *Product Quantity* (columns 3 and 4), and the *Product Price* (columns 5 and 6), respectively. In Panel A, *Product Spending* and *Product Quantity* are recorded as zero when no purchase is made; in such cases, *Product Price* is imputed using the average price paid by other households in the same county, if available. Panel B restricts the sample to Household - Product - Quarter observations with non-zero spending. Standard errors are clustered at the household level. t-statistics are shown in parentheses. Statistical significance at the 10%, 5% and 1% levels is denoted by *, ** and ***, respectively. Detailed variable definitions are available in Appendix Table A.1.

Panel A: Product-Level Regression (Including Zero Consumptions)

	(1)	(2)	(3)	(4)	(5)	(6)
	Product Spending		Product Quantity		Product Price	
Treat×Post	-0.0079**	-0.0080**	-0.0024**	-0.0024**	-0.0059***	-0.0062***
	(-2.46)	(-2.49)	(-2.50)	(-2.51)	(-7.15)	(-6.66)
Observations	234,102,120	234,102,120	234,102,120	234,102,120	78,683,400	68,430,495
Adjusted R-squared	0.183	0.396	0.087	0.340	0.903	0.914
Household FE	Y	N	Y	N	Y	N
Household × Product FE	N	Y	N	Y	N	Y
Time × Product FE	Y	Y	Y	Y	Y	Y

Panel B: Product-Level Regression (Excluding Zero Consumptions)

	(1)	(2)	(3)	(4)	(5)	(6)
	Product Spending		Product Quantity		Product Price	
Treat×Post	-0.0139**	-0.0411***	-0.0006	-0.0084**	-0.0052***	-0.0055**
	(-1.98)	(-3.27)	(-0.27)	(-2.29)	(-3.60)	(-2.53)
Observations	37,749,635	19,011,896	37,749,635	19,011,896	37,749,635	19,011,896
Adjusted R-squared	0.537	0.711	0.198	0.553	0.889	0.913
Household FE	Y	N	Y	N	Y	N
Household × Product FE	N	Y	N	Y	N	Y
Time × Product FE	Y	Y	Y	Y	Y	Y

Table 5. Robustness Check of the Demand and Supply Analysis

This table reports robustness checks for the product-level analysis in Table 4, using a continuous Difference-in-Differences specification and an expanded sample. The sample is extended to include all households and counties available in the Nielsen dataset and incorporates both *Import Exposure* and *Export Exposure* at the household level, as defined in Equation 3. The unit of observation is Household–Product–Quarter, and the sample period spans from 2017Q2 to 2019Q3. The dependent variables are *Product Spending*, *Product Price*, and *Product Quantity*, as in Table 4. The regressions employ the same set of fixed effects. In Panel A, *Product Spending* and *Product Quantity* are recorded as zero if the household did not purchase the product in a given quarter. In these cases, *Product Price* is imputed using the average price paid by other households in the same county, when available. Panel B restricts the sample to Household–Product–Quarter observations with positive spending. Standard errors are clustered at the household level. T-statistics are in parentheses. Statistical significance is indicated by *, **, and *** for the 10%, 5%, and 1% levels, respectively. Detailed variable definitions are provided in Appendix Table A.1.

Panel A: Product-Level Regression (Including Zero Consumptions)

	(1)	(2)	(3)	(4)	(5)	(6)
	Product Spending		Product Quantity		Product Price	
Import Exposure×Post	-0.0132***	-0.0136***	-0.0036**	-0.0037**	-0.0126***	-0.0137***
	(-2.67)	(-2.75)	(-2.43)	(-2.48)	(-9.87)	(-9.60)
Export Exposure×Post	0.0084	0.0087	0.0034*	0.0035*	0.0007	0.0021
	(1.21)	(1.27)	(1.65)	(1.71)	(0.34)	(0.95)
Observations	610,857,567	610,856,515	610,857,567	610,856,515	242,840,541	217,125,275
Adjusted R-squared	0.187	0.396	0.096	0.346	0.912	0.924
Household FE	Y	N	Y	N	Y	N
Household × Product FE	N	Y	N	Y	N	Y
Time × Product FE	Y	Y	Y	Y	Y	Y

Panel B: Product-Level Regression (Excluding Zero Consumptions)

	(1)	(2)	(3)	(4)	(5)	(6)
	Product Spending		Product Quantity		Product Price	
Import Exposure×Post	-0.0263**	-0.0663***	-0.0006	-0.0108*	-0.0103***	-0.0119***
	(-2.39)	(-3.47)	(-0.17)	(-1.89)	(-4.71)	(-3.60)
Export Exposure×Post	-0.0020	0.0136	-0.0018	-0.0042	0.0015	0.0020
	(-0.14)	(0.52)	(-0.40)	(-0.54)	(0.49)	(0.45)
Observations	104,710,638	51,363,523	104,710,638	51,363,523	104,710,638	51,363,523
Adjusted R-squared	0.543	0.716	0.206	0.561	0.891	0.916
Household FE	Y	N	Y	N	Y	N
Household × Product FE	N	Y	N	Y	N	Y
Time × Product FE	Y	Y	Y	Y	Y	Y

Table 6. The Heterogeneity across Household Socio-Economic Characteristics
This table reports the results of the Difference-in-Differences regressions of the percentage change in quarterly household spending on *Treat*, *Post*, and their interaction term. The analysis is based on a panel dataset where each observation is the percentage change in total household spending for household i in quarter t. The dependent variable, *Pct Change*, is calculated relative to each household's average quarterly spending during the pre-trade war period. *Treat* is a dummy variable equal to one if the household belongs to the treatment group. *Post* is a dummy variable equal to one for quarters between 2018Q3 and 2019Q3, and zero otherwise. The sample includes quarterly observations from 2017Q2 to 2019Q3. Panels A and B present subsample analyses by household income and household head age, respectively. In Panel A, households are categorized into three groups based on annual income: less than $30K, between $30K and $100K, and greater than $100K. In Panel B, households are categorized based on the average age of the household head(s): below 35, between 35 and 60, and above 60. In columns (1), (3), and (5), regressions include household fixed effects. In columns (2), (4), and (6), regressions include both Household and Time fixed effects, absorbing variation in both *Treat* and *Post*. Standard errors are clustered at the household level. t-statistics are reported in parentheses. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively. Detailed variable definitions are provided in Appendix Table A.1.

Panel A: Regression Results of Different Income Groups

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable: Pct Change					
	<30k		30k-100k		>100k	
Treat×Post	-0.2143	-0.2267	-1.2080***	-1.2011***	-2.0122**	-1.9946**
	(-0.25)	(-0.27)	(-2.70)	(-2.68)	(-2.37)	(-2.35)
Post	0.7952		0.3835		1.6467***	
	(1.34)		(1.20)		(2.78)	
Observations	42,158	42,158	133,283	133,283	38,175	38,175
Adjusted R-squared	0.137	0.137	0.133	0.134	0.124	0.125
Household FE	Y	Y	Y	Y	Y	Y
Time FE	N	Y	N	Y	N	Y

Panel B: Regression Results of Different Age Groups

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable: Pct Change					
	≤35 yr		35-60 yr		≥60 yr	
Treat×Post	-1.4357	-1.4303	-1.3544***	-1.3422***	-0.8181	-0.8211
	(-0.89)	(-0.89)	(-2.64)	(-2.62)	(-1.60)	(-1.60)
Post	-1.6341		0.4512		1.4029***	
	(-1.43)		(1.22)		(3.91)	
Observations	14,626	14,626	115,701	115,701	83,289	83,289
Adjusted R-squared	0.148	0.167	0.139	0.141	0.110	0.115
Household FE	Y	Y	Y	Y	Y	Y
Time FE	N	Y	N	Y	N	Y

Table 7. The Heterogeneity across Consumption Types

This table reports the results of the triple Difference-in-Differences regressions of total department spending on *Treat*, *Post*, the consumption type dummies. The unit of observation is at the Household–Product Department–Quarter level, differing from that used in Table 2. The analysis is based on a balanced panel dataset, where each observation represents the spending on all products belonging to a specific product department (d) purchased by a household (i) during a given quarter (t). *Treat* is a dummy variable equal to one if the household belongs to the treatment group. *Post* is a dummy variable equal to one for quarters between 2018Q3 and 2019Q3, and zero otherwise. The sample includes quarterly observations from 2017Q2 to 2019Q3. All product departments are classified into one of three mutually exclusive consumption categories: durables, discretionary products, and daily necessities. Regressions include Household × Department Group and Time × Department Group fixed effects. Variations in both *Treat* and *Post* are fully absorbed by the fixed effects. Standard errors are clustered at the household level. t-statistics are reported in parentheses. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively. Detailed variable definitions are provided in Appendix Table A.1.

	(1)	(2)	(3)	(4)
	Dependent Variable: Department Total Spending			
Treat×Post	-0.8607**	-0.5388*	-1.4600**	-0.3809
	(-2.09)	(-1.75)	(-2.55)	(-1.24)
Treat×Post×Durable	-0.4638			-0.9436
	(-0.73)			(-1.47)
Treat×Post×Discretionary		-0.9573**		-1.1152**
		(-1.97)		(-2.24)
Treat×Post×Necessity			1.0791**	
			(2.45)	
Observations	2,097,323	2,097,323	2,097,323	2,097,323
Adjusted R-squared	0.840	0.840	0.840	0.840
Household × Department FE	Y	Y	Y	Y
Time × Department FE	Y	Y	Y	Y

Table 8. The Impact on the Labor Market and Household Wage

This table reports regression results for various labor market outcomes estimated using a Difference-in-Differences framework. Outcomes are regressed on *Treat*, *Post*, and their interaction term. The analysis is based on county-quarter level panel data. Wage is defined as the average weekly wage reported for a given quarter, and employment is the average of monthly employment levels observed during a given quarter. Employment is aggregated across sectors for each county, and wages are computed as employment-weighted averages. *Treat* is a dummy variable equal to one if a county belongs to the treatment group. *Post* is a dummy variable equal to one for quarters between 2018Q3 and 2019Q3, and zero for quarters on or before 2018Q2 . Columns (1), (3), (5), (7), and (9) include County fixed effects. Columns (2), (4), (6), (8), and (10) additionally include Time fixed effects, which absorb variation in both *Treat* and *Post*. Standard errors are clustered at the county level. t-statistics are reported in parentheses. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively. Detailed variable definitions are provided in Appendix Table A.1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	log(Employment)		Wage		log(Wage)		Wage Pct Change		Wage YoY Growth	
Treat×Post	-0.0026	-0.0026	-10.2631***	-10.2650***	-0.0187***	-0.0187***	-1.1287**	-1.1291**	-1.9646***	-1.9645***
	(-0.46)	(-0.46)	(-3.92)	(-3.92)	(-5.60)	(-5.60)	(-2.55)	(-2.55)	(-5.84)	(-5.83)
Post	-0.0300***		40.2238***		0.0570***		1.9053***		6.0735***	
	(-9.31)		(28.01)		(26.60)		(5.49)		(25.55)	
Observations	15,625	15,625	15,625	15,625	15,625	15,625	15,621	15,621	15,625	15,625
Adjusted R-squared	0.995	0.996	0.908	0.921	0.897	0.912	0.108	0.119	0.140	0.258
County FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	N	Y	N	Y	N	Y	N	Y	N	Y

Table 9. The Impact on the Labor Market and Household Wage: Tradable Sectors v.s. Non-Tradable Sectors This table examines the impact of the trade war on labor market outcomes in the tradable and non-tradable sectors separately. Unlike Table 8, which aggregates data across sectors, this table calculates wages and employment separately for the tradable and non-tradable sectors within each county-quarter. Employment is aggregated within the tradable or non-tradable sectors, and wages are computed as employment-weighted averages within each sector. *Treat* and *Post* are defined as in Table 8. *Tradable* is a dummy variable equal to one if the observation corresponds to the tradable sector of a county. Columns (1), (3), (5), (7), and (9) include County and Time (i.e., quarter) fixed effects. Columns (2), (4), (6), (8), and (10) instead control for County × Time fixed effects. Standard errors are clustered at the county level. t-statistics are reported in parentheses. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively. Detailed variable definitions are provided in Appendix Table A.1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	log(Employment)		Wage		log(Wage)		Wage Pct Change		Wage YoY Growth	
Treat×Post×Tradable	-0.0873***	-0.0903***	-13.0289**	-11.2893*	-0.0184***	-0.0171***	-0.0021	-0.0022	-2.2777***	-2.1478***
	(-5.30)	(-5.38)	(-2.30)	(-1.95)	(-3.11)	(-2.87)	(-0.25)	(-0.29)	(-3.69)	(-3.59)
Treat×Post	0.0143**		-1.0835		-0.0033		-0.0038		-0.4018	
	(2.41)		(-0.43)		(-0.94)		(-0.78)		(-1.13)	
Treat×Tradable	1.7296***	1.7243***	157.8125***	157.9039***	0.1634***	0.1636***	-0.0210***	-0.0208***	0.0606	-0.0203
	(38.01)	(37.94)	(12.05)	(12.06)	(12.40)	(12.45)	(-3.91)	(-4.04)	(0.72)	(-0.61)
Post×Tradable	0.0343***	0.0349***	-11.9992***	-14.3870***	-0.0208***	-0.0231***	-0.0175***	-0.0177***	-1.5762***	-1.7367***
	(2.92)	(2.79)	(-2.74)	(-3.20)	(-4.51)	(-4.99)	(-2.70)	(-2.96)	(-3.17)	(-3.63)
Tradable	-2.8742***	-2.8682***	159.3032***	160.1294***	0.1879***	0.1886***	0.0093**	0.0094**	-0.0424	0.0165
	(-89.24)	(-89.01)	(19.16)	(19.18)	(20.75)	(20.81)	(2.14)	(2.28)	(-0.52)	(0.75)
Observations	29,815	28,380	29,815	28,380	29,815	28,380	29,517	27,792	29,761	28,272
Adjusted R-squared	0.945	0.903	0.709	0.553	0.743	0.591	0.059	0.018	0.155	0.161
County FE	Y	N	Y	N	Y	N	Y	N	Y	N
Time FE	Y	N	Y	N	Y	N	Y	N	Y	N
County × Time FE	N	Y	N	Y	N	Y	N	Y	N	Y

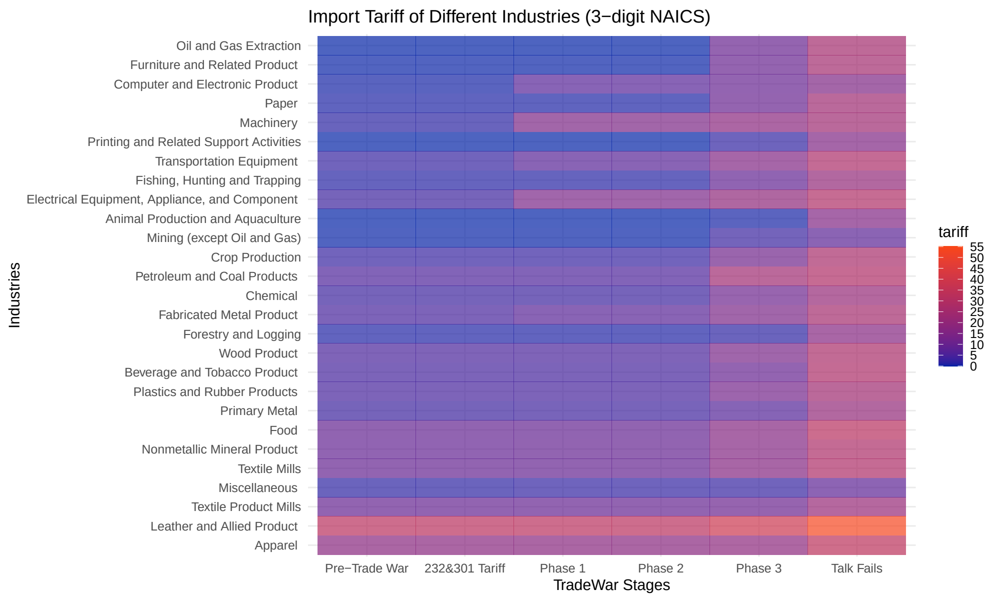
Table 10. The Distribution of Tariffs within Targeted Industries

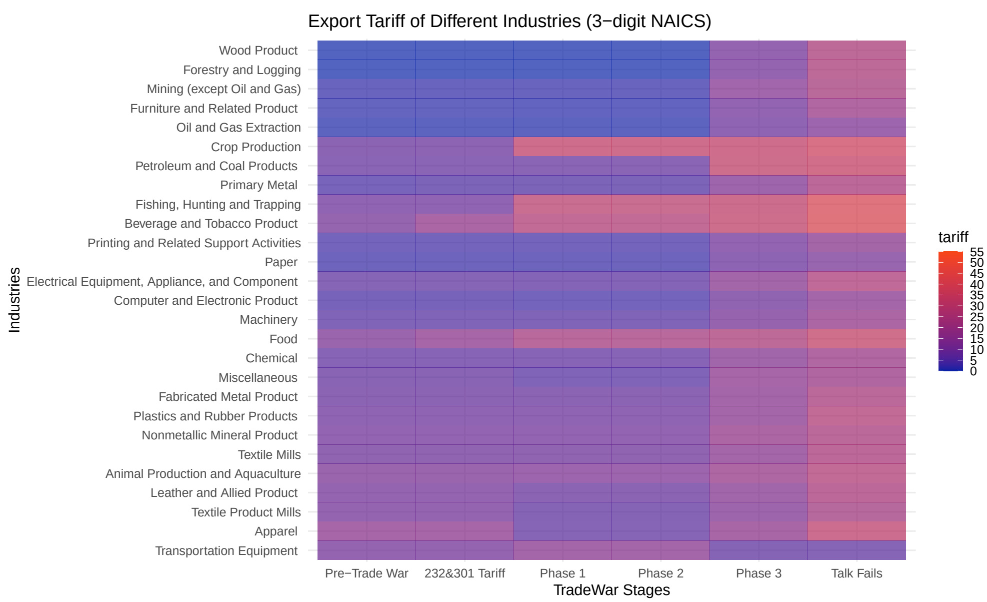
This table presents the results on the triple Difference-in-Differences regressions of household consumption on the *Treat*, *Post*, and the distribution of tariff proxies. The dependent variable, *Quarterly Spending*, is defined as the total dollar amount spent by a household in a given quarter as tracked by NielsenIQ. *Treat* and *Post* are defined as in previous tables. *Capital* is a dummy variable equal to one if a county's capital goods tariff increase is above the median across all sample counties. *Intermediate* and *Consumption* are defined analogously. Standard errors are clustered at the household level. t-statistics are reported in parentheses. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively. Detailed variable definitions are provided in Appendix Table A.1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent Variable: Quarterly Spending							
Treat×Post×Capital	-9.8278	-9.5552					-11.5907	-11.3253
	(-0.34)	(-0.33)					(-0.40)	(-0.39)
Treat×Post×Intermediate			-12.0847	-11.1301			-23.3890	-22.4488
			(-0.34)	(-0.31)			(-0.65)	(-0.62)
Treat×Post×Consumption					24.6178**	24.7689**	26.9713**	27.0627**
					(2.30)	(2.31)	(2.47)	(2.47)
Post×Capital	10.6109	10.5601					13.2457*	13.2152*
	(1.44)	(1.43)					(1.77)	(1.76)
Post×Intermediate			-10.7070	-10.7973			-9.9268	-9.9936
			(-1.22)	(-1.23)			(-1.11)	(-1.11)
Post×Consumption					-11.5494	-11.6605	-12.0255	-12.1237
					(-1.61)	(-1.62)	(-1.63)	(-1.63)
Treat×Post	-7.6347	-7.7585	6.2309	5.4925	-28.0003***	-27.9409***	8.9444	7.9191
	(-0.27)	(-0.27)	(0.18)	(0.16)	(-3.47)	(-3.45)	(0.20)	(0.18)
Post	-30.4864***		-21.1496***		-18.9431***		-26.0980***	
	(-5.03)		(-5.55)		(-4.44)		(-4.11)	
Observations	213,616	213,616	213,616	213,616	213,616	213,616	213,616	213,616
Adjusted R-squared	0.778	0.778	0.778	0.778	0.778	0.778	0.778	0.778
Household FE	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	N	Y	N	Y	N	Y	N	Y

Appendix

Figure A.1. Evolution of the Export and Import Tariff, by Industry



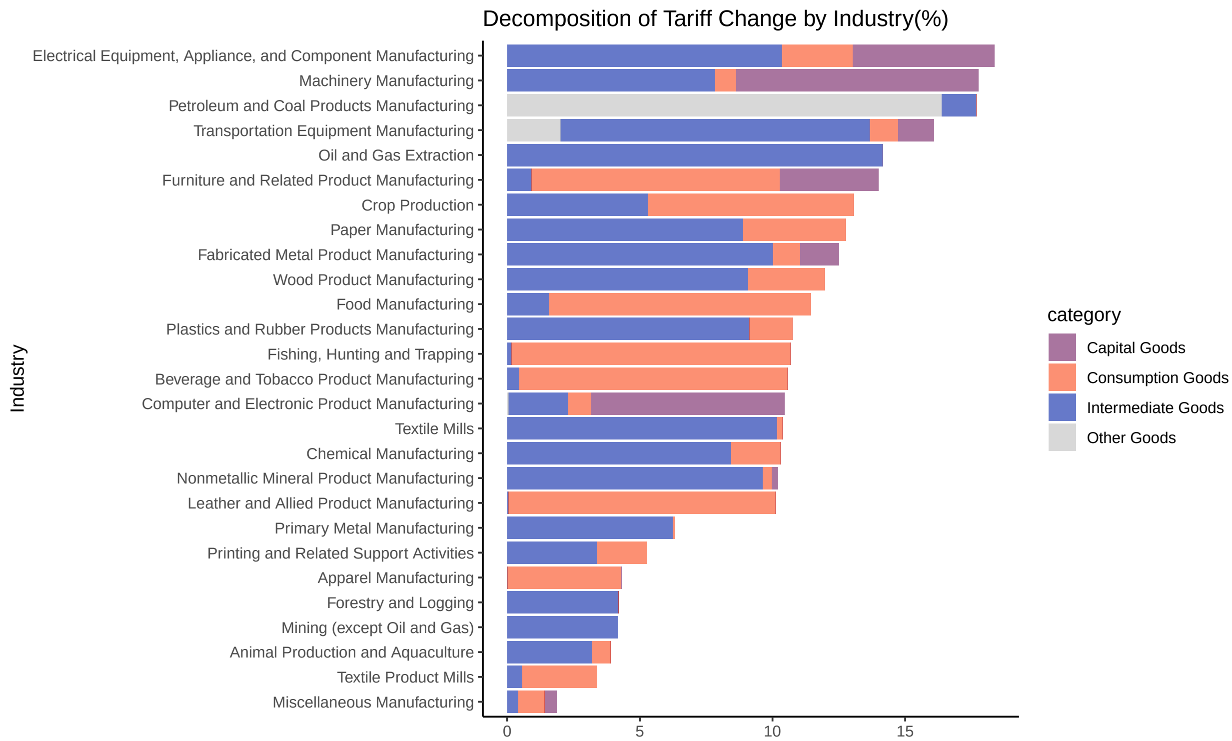


This figure presents the breakdown of import and export (retaliatory) tariff levels across industries (vertical axis) and trade war stages (horizontal axis). Warmer colors (red/orange) indicate higher tariff levels. Panel A reports the tariff levels on goods imported from China to the United States, and Panel B reports the tariff levels levied by China on goods exported from the United States to China. Industries are ranked based on the change in industry-level tariffs, as defined in Equation 1.

Figure A.2. Imports from China

The figures illustrate U.S. imports from China between 1990 and 2024. The top figure shows the composition of imports from China, breaking into capital goods, intermediate goods, consumption goods, and unclassified goods as a percentage of total imports from China over time. The bottom figure shows U.S. imports from China as a percentage of total U.S. imports from the world for these four categories of goods. Vertical dotted lines indicate two key events: 2001, when China joined the WTO, and 2017, when the trade war was about to begin.

Figure A.3. Tariff Increase Decomposition



This figure decomposes the increase in tariffs before and after the trade war, examining the driving forces behind the rise in tariffs across different categories of goods within each industry. The orange bars represent tariff increases on capital goods, the blue bars represent tariff increases on intermediate goods, the purple bars represent tariff increases on consumption goods, and the grey bars represent tariff increases on other goods.

Table A.1. Variable Definitions

Variable name	Description	Source
Quarterly Spending	A household-quarter level variable that equals the total spending by a household in a given quarter.	NielsenIQ
Ln (Spending)	The natural logarithm of Total Spending.	NielsenIQ
Pct Change	The percentage change in a household's total spending in a given quarter, relative to the household's average quarterly spending during the pre-trade war period.	NielsenIQ
YoY Growth	The percentage change in a household's total spending in a given quarter, measured relative to the household's spending in the same quarter of the preceding year.	NielsenIQ
Product Spending	A household–product–quarter level variable that captures the total dollar amount spent by a household on a given product during a specific quarter.	NielsenIQ
Product Price	The average unit price paid by a household for a given product in a specific quarter. If the household does not purchase the product in that quarter, the value is imputed using the average unit price paid by other households in the same county.	NielsenIQ
Product Quantity	A household–product–quarter level variable capturing the total quantity (in units) of a given product purchased by a household in a specific quarter. If the household does not purchase the product in that quarter, the value is set to zero.	NielsenIQ
Treat	A household-level indicator variable equal to one if the household resides in a county with high import exposure during the trade war, while holding export exposure relatively constant.	NielsenIQ and Waugh (2019)
Import Tariff	The import tariff levied by U.S. on Chinese imports.	Waugh (2019)
Export Tariff	The import tariff levied by China on U.S. exports in retaliation.	Waugh (2019)
Import Exposure	The change in EMP-adjusted import tariff levels from the pre–trade war period to the post–trade war period, as defined in Equation 3.	Waugh (2019)
Export Exposure	The change in EMP-adjusted export tariff levels from the pre–trade war period to the post–trade war period, as defined in Equation 3.	Waugh (2019)
<30k	A dummy variable that equals one if the household has an annual income less than 30k.	NielsenIQ
30k-100k	A dummy variable that equals one if the household has an annual income between 30k and 100k.	NielsenIQ

Variable name	Description	Source
>100k	A dummy variable that equals one if the household has an annual income greater than 100k.	NielsenIQ
<35 yr	A dummy variable equals 1 if the age of the household head(s) < 35.	NielsenIQ
35-60 yr	A dummy variable that equals one if one of the household heads is between 35 and 60 years old.	NielsenIQ
>60 yr	A dummy variable equals 1 if the age of the household head(s) > 60.	NielsenIQ
log(Employment)	The natural logarithm of the average monthly employment level in a given county, measured over a specific calendar quarter.	Bureau of Labor Statistics
Wage	The employment-weighted average weekly wage in a given county, measured over a specific calendar quarter.	Bureau of Labor Statistics
log(Wage)	The natural logarithm of Wage.	Bureau of Labor Statistics
Wage Pct Change	The percentage change in a county's Wage relative to its average level in the pre–trade war period.	Bureau of Labor Statistics
Wage YoY Growth	The percentage growth in Wage relative to that observed in the same quarter of the previous year.	Bureau of Labor Statistics
Department Total Spending	A household–department group–quarter level variable measuring the total spending by a household on all products classified under a given department group, as defined by Nielsen.	NielsonIQ
Durable	A dummy variable if the spending made by a household goes into durable products.	NielsonIQ
Discretionary	A dummy variable if the spending made by a household goes into discretionary products.	NielsonIQ
Necessity	A dummy variable if the spending made by a household goes into daily necessities.	NielsonIQ
Capital	A dummy variable that equals one if a county's capital goods tariff increase exceeds the median increase across all sample counties, where capital, intermediate, and consumption goods are classified according to the BEC Revision 5.	UN Trade Statistics and Waugh (2019)
Intermediate	A dummy variable equals one if a county's intermediate goods tariff increase exceeds the median tariff increase across all sample counties.	UN Trade Statistics and Waugh (2019)
Consumption	A dummy variable equals one if a county's consumption goods tariff increase exceeds the median tariff increase across all sample counties.	UN Trade Statistics and Waugh (2019)

Table A.2. Additional Robustness Check

This table reports robustness checks using alternative specifications. We expand the sample to include all counties in the Nielsen data and incorporate both time-varying EMP-adjusted (denoted as E-Adj) import and export tariff levels at the county level. Panel A replicates the analysis in Table 2, using household-quarter level spending as the dependent variable. Panels B and C extend the specification from Table 4, with dependent variables defined at the Household–Product–Quarter level: *Product Spending*, *Product Price*, and *Product Quantity*. The sample covers quarterly observations from 2017Q2 to 2019Q3. *EMP-adjusted Import Tariff* and *EMP-adjusted Export Tariff* represent contemporaneous county-quarter EMP-adjusted tariff levels, as defined in Equation 2. All regressions include the same set of fixed effects as in Table 2 and Table 4. In Panel B, *Spending* and *Quantity* are set to zero for household-product pairs with no purchases in a given quarter; in these cases, *Price* is imputed as the average price paid by other households for the same product in the same county, if available. Panel C restricts the sample to household-product-quarter observations with strictly positive spending. Standard errors are clustered at the household level. T-statistics are reported in parentheses. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively. Detailed variable definitions are provided in Appendix Table A.1.

Panel A: Household Quarterly Spending

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Quarterly Spending		Ln (Spending)		Pct Change		YoY Growth	
log(1+Import E-Adj Tariff)	-64.6737***	-24.0796***	-0.0513***	-0.0202***	-2.9157***	-2.1133***	-10.1042***	-2.6369***
	(-11.72)	(-3.45)	(-11.57)	(-3.60)	(-7.29)	(-4.16)	(-13.78)	(-2.97)
log(1+Export E-Adj Tariff)	-15.6398**	-0.0038	-0.0300***	0.0007	1.0594*	0.0858	-0.6301	0.4084
	(-2.09)	(-0.00)	(-4.99)	(0.10)	(1.96)	(0.14)	(-0.64)	(0.36)
Observations	596,427	596,427	596,427	596,427	569,803	569,803	494,912	494,912
Adjusted R-squared	0.795	0.795	0.770	0.770	0.136	0.137	0.110	0.113
Household FE	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	N	Y	N	Y	N	Y	N	Y

Panel B: Product-Level Regression (Including Zero Consumptions)

	(1)	(2)	(3)	(4)	(5)	(6)
	Product Spending		Product Quantity		Product Price	
log(1+Import E-Adj Tariff)	-0.0146***	-0.0151***	-0.0037***	-0.0038***	-0.0110***	-0.0113***
	(-3.14)	(-3.27)	(-2.68)	(-2.74)	(-8.96)	(-8.24)
log(1+Export E-Adj Tariff)	0.0111*	0.0112*	0.0035**	0.0036**	-0.0031*	-0.0028
	(1.90)	(1.93)	(2.01)	(2.08)	(-1.92)	(-1.48)
Observations	610,857,567	610,856,515	610,857,567	610,856,515	242,840,541	217,125,275
Adjusted R-squared	0.187	0.396	0.096	0.346	0.912	0.924
Household FE	Y	N	Y	N	Y	N
Household × Product FE	N	Y	N	Y	N	Y
Time × Product FE	Y	Y	Y	Y	Y	Y

Panel C: Product-Level Regression (Excluding Zero Consumptions)

	(1)	(2)	(3)	(4)	(5)	(6)
	Product Spending		Product Quantity		Product Price	
log(1+Import E-Adj Tariff)	-0.0265**	-0.0586***	-0.0014	-0.0110**	-0.0086***	-0.0090***
	(-2.57)	(-3.25)	(-0.45)	(-2.07)	(-4.19)	(-2.92)
log(1+Export E-Adj Tariff)	-0.0037	0.0097	-0.0016	-0.0006	-0.0018	-0.0026
	(-0.30)	(0.45)	(-0.42)	(-0.10)	(-0.74)	(-0.69)
Observations	104,710,638	51,363,523	104,710,638	51,363,523	104,710,638	51,363,523
Adjusted R-squared	0.543	0.716	0.206	0.561	0.891	0.916
Household FE	Y	N	Y	N	Y	N
Household × Product FE	N	Y	N	Y	N	Y
Time × Product FE	Y	Y	Y	Y	Y	Y

Table A.3. Additional Cross-sectional Analysis on Consumption Response
This table presents subsample regressions based on the specification in Column (4) of Table 7, examining heterogeneity in treatment effects across household income and age groups. Columns (1)–(3) report results for households with annual income above below \$30K, between \$30K and \$100K, and above \$100K, respectively. Columns (4)–(6) report results for households aged below 35, between 35 and 60, and above 60, respectively. Standard errors are clustered at the household level and reported in parentheses. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively. Detailed variable definitions are provided in Appendix Table A.1.

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable: Department Total Spending					
	Income			Age		
	<30k	30-100k	>100k	≤35 yr	35-60 yr	≥60 yr
Treat×Post	-0.0924	-0.2181	-1.0739	-0.4445	-0.1346	-0.5120
	(-0.15)	(-0.56)	(-1.30)	(-0.34)	(-0.30)	(-1.23)
Treat×Post×Durable	-0.4068	-0.7885	-2.8898**	-1.9368	-0.7490	-1.2956*
	(-0.39)	(-1.25)	(-2.30)	(-1.00)	(-1.03)	(-1.84)
Treat×Post×Discretionary	0.4102	-0.9221	-2.6376*	1.9360	-1.8425**	-0.2956
	(0.31)	(-1.12)	(-1.65)	(0.85)	(-2.09)	(-0.29)
Observations	408,556	1,310,410	378,357	144,460	1,139,347	813,516
Adjusted R-squared	0.836	0.842	0.833	0.786	0.835	0.857
Household × Department FE	Y	Y	Y	Y	Y	Y
Time × Department FE	Y	Y	Y	Y	Y	Y