The Consumption Response to Protectionism*

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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 where local firms heavily rely on intra-industry inputs, and when protective tariffs target capital rather than consumption goods. Our findings underscore the vertical integration of U.S. and Chinese firms within tariff-targeted industries. Protectionism does not necessarily benefit domestic firms and may risk local household welfare.

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1 Introduction

The re-election of President Donald Trump on November 5, 2024, and his renewed pledge to impose "horrible" new tariffs on imports, has ignited broad concerns over the resurgence and intensification of protectionist trade policies.[1] The trade disputes initiated during Trump's earlier term — targeting China, the European Union, and other major trading partners — represented a pivotal shift in the trajectory of global trade. These actions have had lasting geopolitical and economic consequences, with effects that continue to reverberate through 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 attributed large-scale layoffs to tariffs on Electronics, Aluminum, and Toys - their home industries, respectively[2][3][4]. 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 Auto import tariffs, potentially boosting domestic employment and

[1]See details at https://www.cnbc.com/2024/11/06/companies-race-to-get-imports-to-us-with-trump-win-vow-on-new-tariffs.html.

[2]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

[3]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.

[4]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.

household wealth[5]. 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 associated 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 could affect household consumption through four distinct, yet interrelated, channels. First, consumption might increase as a result of a positive income shock from the protection of domestic industries (Pierce and Schott, 2016; Caliendo, Dvorkin, and Parro, 2019; Autor, Dorn, and Hanson, 2021). On the other hand, consumption could decrease due to a negative income shock caused by rising costs of imported inputs for local firms (Bellora and Fontagné, 2020; Flaaen and Pierce, 2024). Furthermore, retaliatory tariffs imposed by foreign nations in response to U.S. protectionism may lead to reductions in consumption (Waugh, 2019). Lastly, even in the absence of direct income shocks, the pass-through of protective tariffs to retail prices or margins may alter supply dynamics - increasing prices and reducing availability of products (Ma et al., 2024), which result in a contraction of household consumption (Fajgelbaum et al., 2020; Cavallo et al., 2021). This study is among the first to assess and disentangle the conflicting predictions

[5]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/

from the first two channels, while rigorously controlling for the well-documented impacts of the third (retaliatory tariffs) and fourth (pass-through) 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 $1,345, and the average annual growth rate of per capita Personal Consumption Expenditures 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 third 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 those of Blanchard, Bown, and Chor (2024), who document limited electoral gains for the Republican party in counties receiving greater U.S. tariff protection during the 2018 midterm elections.

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 fourth mechanism). Specifically, import tariffs may compress retail margins, thereby limiting product availability, or increase retail prices, leading to a contraction in supply (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 1.23% reduction in the year-on-year growth rate, is both statistically and economically significant. The effects on wages are more pronounced in regions where a larger share of the local labor force is employed in tradable sectors, rather than in non-tradable sectors. In addition, we analyze changes in employment levels 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 reveals that the income shock of the trade war is disproportionately borne by working-class Americans. The results are not statistically significant among the lowest income group and younger households. Households appear to adjust their consumption by reducing expenditures on non-essential items such as Health and Beauty products, while maintaining spending on necessities like Dairy Products, Fresh Produce, and Meat. This differential adjustment in spending underscores the impact of the trade war on discretionary consumption, with essential goods remaining relatively unaffected.

The remainder of this study examines the sources and underlying mechanisms of this income shock. The existing literature on the *China Shock* 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 composition of Chinese imports, which have shifted from consumer goods such as furniture, apparel, and footwear to intermediate and capital goods (Handley, Kamal, and Monarch, 2025). For example, many U.S. firms have offshored production to China, maintaining brand ownership and design capabilities while outsourcing manufacturing. The importation of these offshore-produced goods is often classified as intra-industry trade of the parent firm. Additionally, U.S. firms across various sectors, including pharmaceuticals, rely on upstream inputs from Chinese supply chains, such as key starting materials and Active Pharmaceutical Ingredients (APIs). While the initial phase of trade integration primarily exposed domestic industries to *same industry* competition from Chinese imports, the more recent phase of trade unwinding has instead contributed to the fragmentation of *same industry* supply chains. In this context, Wang et al. (2018) highlight that a supply-chain perspective reveals how Chinese imports can, in fact, bolster local employment and wages. 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.

To further investigate this potential asymmetry from the perspective of vertical integration, we examine whether our findings are sensitive to both 1) the distribution of tariffs and 2) the structure of upstream inputs used by local firms. 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 consumer 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. Furthermore, our analysis shows that when local firms rely more heavily on the inputs sourced from the same industry, the treatment effects are stronger. 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 research contributes to two key strands of literature in the intersection of finance and international economics. The first addresses the competitive effects of trade integration and their implications for employment and household welfare. A substantial body of work has documented the displacement effects associated with increased import competition, particularly from China, highlighting 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 particular, Barrot et al. (2022) provide evidence that household debt levels surged following 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. While much of the existing research has concentrated on retaliatory tariffs (Waugh, 2019) or on supply-side factors by assessing pass-through effects on household welfare (Amiti et al., 2020; Fajgelbaum et al., 2020; Cavallo et al., 2021), our study diverges by focusing on a distinct research question. In particular, Ma et al. (2024) utilizes the same NielsenIQ database but investigates the impact of supply-side factors, examining the channels of price and product variety on consumer cost of living. In contrast, our analysis explores the demand-side implications of protective tariffs, thereby identifying a novel income channel within vertically integrated industries, while rigorously accounting for the effects of price pass-through and retaliatory tariffs.

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, geographic regions, and the broader economy (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 sharply in 2018, following years of simmering trade disputes. In 2017, the U.S. initiated investigations under Section 232 (national security) and Section 301 (unfair trade practices) of the Trade Act of 1974, targeting steel, aluminum, and China's trade and industrial policies.

On March 22, 2018, President Trump directed the U.S. Trade Representative (USTR) to propose tariffs on $50–60 billion of Chinese goods under Section 301. The USTR released a $50 billion list on April 3, 2018, targeting advanced technology sectors such as aerospace, medical devices, and semiconductors. China retaliated on April 2 and 4, 2018, with a $50 billion list targeting U.S. agricultural exports (e.g., soybeans, pork) and manufactured goods (e.g., automobiles, airplanes). Chinese firms also halted purchases of U.S. agricultural products.

On July 6, 2018, *Phase 1* of the trade war began. Both sides implemented 25% tariffs on $34 billion of their $50 billion lists. On August 23, 2018, *Phase 2* of the trade war started with 25% tariffs levied on the remaining $16 billion of goods on both sides' lists. On September 18 and 19, the U.S. introduced a new $200 billion list and planned to raise their tariffs to 5% to 10% and further increase them to 25% by January 2019. And China announced its new list of $60 billion with new tariffs ranging between 5% to 10%. *Phase 3* of the trade war started on September 24, with the new lists of goods being implemented.

On December 1, 2018, the U.S. postponed tariff increases and agreed to negotiate, leading to a temporary tariff. Both sides agreed to work toward a negotiated settlement with a deadline of March 2019. But talks collapsed in May 2019. On May 10, 2019, the U.S. raised tariffs from 10% to 25% on $200 billion of Chinese imports. China responded on June 1, 2019, with tariffs up to 25% on $60 billion of U.S. goods.

On June 29, 2019, during the G20 Osaka Summit, both sides agreed to pause further tariffs amid resumed negotiations. However, the negotiation collapsed again and tensions reignited in August 2019 when the U.S. announced plans to raise tariffs on \$250 billion of Chinese goods to 30% and impose 15% tariffs on an additional \$300 billion. On September 1, 2019, part of the new tariff went into effect - the tariff of about \$112 billion of Chinese imports was raised to 15%. In response, on August 23, 2019, China retaliated with tariffs on \$75 billion of U.S. goods that went into effect on September 1, 2019.

On December 13, 2019, the U.S. and China reached a preliminary agreement, avoiding planned December 15 tariff increases. The *U.S.-China Phase One Trade Deal* was signed on January 15, 2020, and included commitments from China to increase purchases of U.S. goods. However, the majority of the tariffs imposed since 2018 remain in effecty. [6]

2.2 The Distributional Impacts of the Trade War across Industries

In this subsection, we analyze the effects of the trade war, detailing its economic impact across various industries. Figure A.1 illustrates the evolution of the import and export tariff rates by industries (3-digit NAICS code). The heat maps show the tariff rates at six snapshots along the trade war: Pre-Trade War, 232 & 301 Investigation, Phase 1, Phase 2, and Phase 3, and Trade Talk Fails. The heat maps show that Computer and Electronic Products, Machinery, Transportation Equipment, Electrical Equipment, Appliance and Component, are among the first few industries targeted by the United States. In retaliation, Crop, Fishing and Hunting, Food, Beverage and Tobacco, Apparel, Leather, and Transportation Equipment, are the early targets of China.

Figure 1 provides a detailed analysis of tariff adjustments across industries in the context of the trade war. The figure captures three key dimensions: (i) the change in industry-level tariff rates, computed using Equation 1; (ii) a comparison of pre-trade war tariff rates with those in effect as of September 2019; and (iii) industry-specific trade volumes for U.S. imports

[6] 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)

from, and exports to, China in 2017. The upper panel illustrates the evolution of U.S. import tariffs on Chinese goods, while the lower panel presents the corresponding changes for U.S. exports to China. Industries are ranked by the magnitude of tariff adjustments observed during the trade war.

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

In Equation 1, we use the tariff rates in December 2017 as the tariff rates before the trade war ($\tau_{s,201712}$) , and the average monthly tariff rates of each industry between July 2018 and December 2019 as the post-trade war tariffs ($\tau_{s,post}$). s is the 3-digit NAICS industries and t is the month.[7]

Figure 1 highlights that industries such as Oil and Gas Extraction, Computer and Electronics, Machinery, Printing, Transportation, and Electrical Equipment, which are primarily engaged in heavy industry and capital goods production, experienced the most pronounced increases in import tariffs. Conversely, industries producing lighter industrial goods, such as Textiles, Leather, and Apparel, faced comparatively smaller tariff hikes. The middle column of the figure indicates that pre-trade war tariff levels were relatively uniform across these sectors, suggesting that the disparity in tariff impacts is largely attributable to post-trade war tariff escalations.

Furthermore, import data from China indicate that industries subject to both the largest and smallest tariff increases exhibited comparable trade volumes. For instance, the Computer and Electronic Products sector—the largest category of U.S. imports from China—experienced the third-highest tariff hike. On the export side, industries facing the most substantial tariff increases typically accounted for a smaller share of U.S. exports to China in 2017, prior to the onset of the trade war.

[7]Some tariffs of certain industries are 0, so $log(1 + \tau)$ is used in the equation.

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

3.2 Trade War Tariff Data

We construct three tariff-based measures to capture 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, $\tau_{s,t}$, is then computed as the trade volume-weighted sum of the HS6 tariffs within each three-digit NAICS industry.

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 tariff level ($\tau_{c,t}$) 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

[8] The data and methodology are downloaded from https://www.tradewartracker.com/, and we thank the author for kindly sharing the data publicly. Note that Waugh (2019) build the measures based on retaliation tariff, while we adopt the methodology for the protective (import) tariff.

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 United States. 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 of the EMP-adjusted tariffs 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 investigation, and the response from China. In July 2018, the trade war broke out and by the end of Phase 3 of the trade war, the average EMP-adjusted tariff level for U.S. imports from China had rapidly increased by almost 250%, and the average EMP-adjusted tariff level for U.S. exports to China had tripled. 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 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 $\tau_{c,201712}$, 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 $\tau_{c,\text{post}}$. The change in county-level EMP-adjusted import tariff level, $Import\ Exposure_c$, is calculated as:

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

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 and trade war exposure measures. We classify households into treatment and control groups based on their county-level exposure to Chinese imports. 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.

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 102,791 household-quarter observations from 11,562 treatment-group households and 109,741 observations from 12,363 control-group households. The average quarterly spending in the treatment group is $1,345 - approximately $4 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 September 2019 ($\tau_{c,post}$). Both measures are expressed as percentages.

The sample includes 571 treatment counties and 993 control counties. In Panel A, the mean of *Pre-TW EMP-Adjusted Import Tariff* is 0.794, rising to 3.636 in the post-trade war period. In contrast, in Panel B, the corresponding values are from 0.225 to 0.649, 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 change of *Post-TW EMP-Adjusted Import Tariff* relative to the *Pre-TW EMP-Adjusted Import Tariff*, which is defined in Equation 4. *Import Exposure* is the critical measure we use to construct our treatment and control groups. Table 1 shows that the mean (median) of *Import Exposure* in the treatment group is 0.909 (0.889) and the mean (median) of *Import Exposure* in the control group is 0.251 (0.269). That is, the treatment group has a larger *Import Exposure* on average.

4 Identification Strategy

4.1 Identification Challenges

We examine whether and how protective U.S. import tariffs affect household consumption. Four identification challenges arise when examining the effects of the trade war. First, the trade war influences consumer consumption through multiple channels. Increased import tariffs may be passed on to consumers, raising prices and affecting spending through a price effect. Additionally, consumer income could be impacted by both U.S. import tariffs and retaliatory tariffs imposed by China on U.S. exports. Disentangling these channels is critical.

Second, tariffs are imposed at the product or industry level and represent a national policy applied uniformly across all regions. This necessitates identifying regional variations in exposure to tariffs.

Third, the trade war escalated rapidly over a short period. However, most macroeconomic indicators, such as GDP, are available only at yearly intervals or at the state level, limiting their ability to provide timely evidence of the trade war's effects.[9]

Lastly, the consumption we observe is an equilibrium outcome jointly determined by supply and demand. On the supply side, higher tariffs could limit product availability, increase retail prices, and shift the supply curve upward, leading to reduced consumption. However, decreased consumption could also result from demand-side contraction, if tariffs harm local businesses, reduce wage income, and weaken consumer demand. Both mechanisms can lead to reduced consumption and likely occur simultaneously. Our goal is to examine which factor plays a larger role.

[9] For example, the Bureau of Economic Analysis provides quarterly state-level GDP and yearly county-level GDP.

4.2 Identification Strategy

To address these challenges, we employ a difference-in-differences (DiD) approach and construct treatment and control groups based on cross-county variation in exposure to tariffs, following Waugh (2019). Although the same industry faces identical tariff changes nationwide, counties differ in their industrial composition and employment structure, leading to varying levels of exposure. For example, if the Machinery industry experiences a large increase in import tariffs, a county with a higher proportion of its workforce in Machinery will face a greater impact than a county where Machinery represents a smaller share of employment. Similarly, a county with significant agricultural employment will be more affected by China's retaliatory tariffs on U.S. agricultural exports.

We first calculate a county-month level tariff as defined in Equation 2. Both import and export tariffs are computed for each county. To measure the severity of the trade war's impact, we compare pre- and post-trade war tariffs. The pre-trade war tariff for county c is defined as $\tau_{c,201712}$, representing the county's tariff in December 2017. The post-trade war tariff is the average monthly tariff from July 2018 to December 2019, denoted $\tau_{c,\text{post}}$. The change in county-level import tariffs, $import\_exposure_c$, is calculated as:

$$import\_exposure_c = \log(1 + \tau_{c,\text{post}}) - \log(1 + \tau_{c,201712}). \tag{4}$$

A similar measure, $export\_exposure_c$, captures changes in retaliatory tariffs imposed by China on U.S. exports. Together, $import\_exposure_c$ and $export\_exposure_c$ reflect geographic variation in the severity of the trade war's impacts. For example, a larger $import\_exposure_c$ indicates that County c experienced a greater increase in import tariffs on Chinese goods.

Next, we divide approximately 60,000 households from Nielsen into quintiles based on $export\_exposure$ and further split each quintile into five $import\_exposure$ groups, creating 25 groups in total (5×5). Households from counties with the smallest and largest *import_exposure* within each *export_exposure* quintile form the control (*Import Smallest*) and treatment (*Import Largest*) groups, respectively. This approach isolates the effects of import exposure by controlling for export exposure. The treatment group consists of 11,562 households from 571 counties, and the control group consists of 12,363 households from 993 counties. Summary statistics in Table 1 indicate that the treatment group has higher *import_exposure*, with a mean (median) of 0.909 (0.889) compared to 0.251 (0.269) in the control group. The treatment group also has slightly higher *export_exposure*, though the difference is smaller: 0.563 (0.483) versus 0.357 (0.385). Figure 5 shows the geographic distribution of households in both groups.

Our primary dependent variable is household quarterly spending. Figure 6 plots the average ln(*Spending*) for both groups. The raw data reveal comparable pre-trade war spending levels, with the treatment group exhibiting lower consumption 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:

$$\begin{aligned} Total\_Spending_{i,t} = &\beta_1 Treat + \beta_2 Post + \\ &\beta_3 Treat \times Post + FEs + \epsilon_{i,t} \end{aligned} \tag{5}$$

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

Here, β_3 captures the DiD effect. Household and time fixed effects control for unobserved household heterogeneity and seasonality.

The DiD approach addresses three key challenges. First, it isolates the income effect caused by import tariffs by ruling out price effects (tariffs apply uniformly, so treatment and control groups face similar price impacts) and income effects from retaliatory tariffs (via comparison of counties with comparable $export\_exposure$). Second, it exploits geographic variation in tariff exposure, a strategy widely used in prior work (Autor, Dorn, and Hanson, 2013; Waugh, 2019). Third, the granularity and high frequency of Nielsen data allow tracking immediate consumption responses to the trade war's escalation.

4.3 Demand-Side vs. Supply-Side Channels

A remaining empirical challenge is determining whether demand contraction or supply reduction drives the observed changes in consumption. Increased import tariffs raise prices of imported goods by shifting the supply curve upward, leading to a drop in consumption—similar to the effect of a negative demand shock. However, the supply-side channel is unlikely to be the primary driver of our results. First, Figure 2 shows that nearly 50% of consumption in the Nielsen Data consists of deli, fresh produce, dry grocery, and dairy products—goods predominantly produced domestically or locally, which are largely unaffected by import tariffs directly.

Second, we conduct product-level analysis to distinguish between demand-side and supply-side effects by leveraging their differing price implications. While both a downward shift in the demand curve and an upward shift in the supply curve reduce equilibrium consumption, demand contraction lowers prices, whereas supply reduction raises them. By observing directional changes in product spending, quantity purchased, and unit prices, we examine whether demand-side or supply-side forces dominate. Third, in Equation 6, we control for $Time \times Product$ and $Household \times Product$ fixed effects to compare consumption of identical products across households at the same time, isolating demand effects from supply-side price changes caused by tariff passthrough.

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

5 Results

5.1 Baseline Regressions

Table 2 shows our baseline results. In this table, we regress the quarterly household spending on the *Treat*, *Post*, and the interaction term in a Difference-in-Differences setting. Each observation is the total spending of a household (i) in quarter (t). *Quarterly Spending* is the total dollar value spent by a household tracked by Nielsen IQ. *Treat* is a dummy variable that turns on when the household is in the treatment group. We only include the quarterly observations from Q2 2017 to Q3 2019. The *Post* is a dummy variable that equals one for every quarter t that falls between Q3 2018 and Q3 2019, and equals zero for every quarter t observed on or before 2018 Q2. The dependent variables are *Quarterly Spending* (Columns 1 and 2), *Ln*(*Spending*) (Columns 3 and 4), and the *Pct Change* in total spending (Columns 5 and 6), respectively. $Pct\ Change_{c,t}$ is the relative change of the *Quarterly Spending* in that quarter to the average of pre-treat war quarterly spending. In Columns 1, 3, and 5, we include the household fixed effects. In Columns 2, 4, and 6, we include both the household and quarter fixed effects that absorb the variations in both *Treat* and *Post*. By including the quarter 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 \$14.0564 less than the control group households each quarter due to the trade war. In Columns 3 and 5, the results also indicate that the treatment group households reduced consumption by 1.11% (Column 3) or 1.23% (Column 5) more than the control group households due to the trade war. In Columns 2, 4, and 6, the specification including both household and quarter fixed effects yield quantitatively similar results. All the coefficients are significant at the 1% level. Besides, the coefficients of the dummy variable $Post$ are negative when available, suggesting that the trade war has an overall negative impact for both groups.

The negative impact on consumption is economically significant as well. The coefficients in Column 1, \$14.0564 are about 1.05% of the sample mean of treatment group households' quarterly spending (\$1,345). Coefficients from other columns also suggest that the magnitude of the lower consumption is between 1.11% and 1.23%. As a comparison, the average annual change rate of the Personal Consumption Expenditures per capita between 2008 and 2017 is 2.34%[11].

We also carry out a dynamic analysis of the trade war impact. Instead of using the dummy variable $Post$ in Equation 5, we create 9 dummy variables indicating different quarters from 2017 Q3 to 2019 Q3, and we use 2017 Q2 as the benchmark. We also create the interaction terms between these quarter dummies and $Post$ and the new specification is in 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 plotted in Figure 7.

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

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

Figure 7 first indicates that prior to the commencement of the trade war in July 2018, the coefficients fluctuate around zero and lack statistical significance. The consumption patterns of both the treatment and control groups exhibit parallel trends before the outbreak of the trade war. Second, Figure 7 further illustrates that the adverse effects of the trade war on consumption primarily became evident in 2019, rather than during the initial phase of the conflict. This delay in impact could be attributed to both the time it takes for tariffs to influence consumption and the gradual escalation of tariffs over time. Initially, only $50 billion worth of imports from China faced an increased tariff of 25%, constituting a small proportion of the total import value, which stood at $505.17 billion in 2017. A significant development occurred in late September 2018 when an additional $200 billion worth of goods were added to the tariff list. Despite this substantial increase, the tariffs remained at 5% to 10%. Expectations also played a pivotal role. Trade disputes between the U.S. and China were not uncommon, and both countries expressed their intention to reach a truce through negotiations after Phase 3 of the trade war. The planned tariff increase to 25% on the $200 billion goods in early December 2018 was eventually postponed. Therefore, perhaps at that time, very few anticipated the escalation to such a serious extent.

5.2 Disentangling the Demand and Supply Effects

The reduction in consumption resulting from the trade war could be caused by the downward shift of the demand curve, the upward shift of the supply curve, or, more likely, a combination of both. We aim to disentangle which factors play a dominating role by analyzing not only the change in consumption but also the quantity and price.

We construct a panel dataset representing household i's consumption on product p in quarter t including total spending, the quantity of products, and the price ($Spending_{i,p,t}$, $Quantity_{i,p,t}$, $Price_{i,p,t}$). If a household does not spend any money on a product in that quarter, both $Spending_{i,p,t}$ and $Quantity_{i,p,t}$ 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 $Spending_{i,p,t}$ and $Quantity_{i,p,t}$ are zero, we use the average price of other households in that county for the quarter as $Price_{i,p,t}$. As a robustness check, we also report regression results on a dataset excluding observations with zero consumption. The specification is in Equation 6.

Table 3 shows these results. In Columns 2, 4, and 6, we include $Household \times Product$ fixed effect and $Time \times Product$ fixed effect so we are comparing different households' consumption of the same goods. Panel A shows the results on the panel dataset including zero consumptions. Relative to the control group, the product spending of the treatment group is lower by \$0.0075 after the outbreak of the trade war, which is 0.72% of the sample mean (\$1.047). The quantity is lower by 0.0023, which is 0.76% of the sample mean (0.3). The price is lower by \$0.0063, which is 0.18% of the sample mean (\$3.557). Panel B shows the results on the panel data excluding zero consumptions. Relative to the control group, the product spending of the treatment group is lower by \$0.0386 after the outbreak of the trade war, which is 0.61% of the sample mean (\$6.321). The quantity is lower by 0.008, which is 0.44% of the sample mean (1.812). The price is lower by \$0.0058, which is 0.15% of the sample mean (\$3.858). We include the $Household$ fixed effect instead of the $Household \times Product$ 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 dominant 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.

5.3 Robustness Check

In the DiD analysis presented above, we observe that counties in the treatment group – those experiencing more substantial increases in protective import tariffs – exhibit lower consumption levels relative to the control group counties following the onset of the trade war. Furthermore, the observed results appear to be driven more by a contraction in demand rather than supply constraints. This suggests that the import tariffs do not provide the intended protective effect but rather diminish local consumption power.

In this section, we assess whether the findings from the DiD analysis are applicable beyond the treatment and control groups to all counties. The DiD analysis compares consumption in counties with similar changes in export tariffs (i.e., import tariffs imposed by China on U.S. exports) but differing import tariff changes. Although this method isolates the effects of export tariffs and highlights the impact of import tariffs, it raises concerns about external validity. To address this, we examine the effects of both import and export tariffs across all counties in the U.S. We incorporate both the import and export tariffs of each county i as independent variables, represented by $\log(1+ImportTariff_{i,t})$ and $\log(1+ExportTariff_{i,t})$. We conduct analyses similar to those in Table 2 and Table 3, investigating the effects of import and export tariffs on total spending as well as on product-level spending, quantity, and price for the contemporaneous quarter. The sample period spans from 2017 Q2 to 2019 Q3.

Our findings reveal that increased import tariffs negatively impact consumption, whereas the effects of export tariffs imposed by China are not statistically significant. These results are detailed in Table 4. In Panel A, we examine quarterly household spending, controlling for either household fixed effects or both household and time (quarter) fixed effects. In Column (2), where both quarter and household fixed effects are controlled for, a one-percent increase in the county-level import tariff results in a \$23.34 decrease in quarterly spending, which constitutes approximately 1.76% of the sample mean (\$1325.92). Columns (4) and (6) show that a one-percent increase in import tariffs leads to a 2% decrease in quarterly spending, or a 2.075% reduction compared to average household spending before the trade war began around mid-2018. Meanwhile, the export tariff—referring to Chinese import tariffs on U.S. exports—shows a negative impact in most regressions, suggesting that retaliatory tariffs imposed by China also undermine U.S. consumer purchasing power. However, the effects of the export tariff are insignificant at the 10% level across all regressions.

In Panels B and C of Table 4, we perform similar product-level regressions as those in Table 3. Panel B includes zero-consumption observations, as in Panel A of Table 4. The results indicate that increased import tariffs negatively affect product spending, quantity, and prices. When controlling for $Household \times Product$ fixed effects and $Time \times Product$ fixed effects, a one-percent increase in the import tariff results in a \$0.013 decrease in spending, a 0.003 decrease in quantity, and a \$0.01 decrease in price per product, which are approximately 1.16%, 0.94%, and 0.28% of the sample mean for each variable (\$1.12, 0.32, and \$3.59 respectively). In Panel C, where zero-consumption observations are excluded, the coefficients for regressions controlling for $Household \times Product$ fixed effects and $Time \times Product$ fixed effects show that a one-percent increase in import tariffs leads to a \$0.057 decrease in spending, a 0.011 decrease in quantity, and a \$0.009 decrease in price per product, which are about 0.76%, 0.58%, and 0.22% of the sample mean for each variable (\$7.51, 1.91, and \$4.09 respectively). While evidence on the effects of export tariffs is mixed, in all preferred specifications that include both $Household \times Product$ and $Time \times Product$ fixed effects, the coefficients on the export tariff remain insignificant, indicating that Chinese import tariffs do not significantly affect U.S. consumers. These findings corroborate our previous conclusion that the negative impact of increased import tariffs is more attributable to reduced demand rather than supply constraints.

5.4 Cross-Sectional Analysis

5.4.1 Household Social-Economic Profiles

In Table 5, 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 5.

In Panel A, households are categorized by income: those earning less than 30K, between 30K and 50K, between 50K and 100K, and above 100K annually. Treatment groups in all income brackets experienced a reduction in consumption relative to the control groups after the trade war, though the reduction is not significant in the lowest income group (income less than 30K). The magnitude is also smaller for the lowest income group, with a coefficient of -0.376%, which is less than other income groups where coefficients range between -0.961% and -1.917%.

In Panel B, households are categorized into three groups: the Boomer Generation, Generation X, and the Millennials. Specifically, $Generation\,B$ represents households whose household head was born between 1946 and 1964. Similarly, $Generation\,X$ comprises households with a head born between 1965 and 1980, and $Generation\,M$ includes households with a head born between 1981 and 1996. All effects are negative across all groups, although the results for the Millennials group are insignificant, possibly due to the smaller sample size.

Overall, our findings indicate that middle or high-income households, and middle-aged and older households, bear a greater burden from the trade war. This also suggests that the reduction in total spending may not be driven solely by rising prices due to tariffs, as price inflation typically affects low-income groups more.

5.4.2 Department Groups

In this section, we delve into how household consumption patterns are influenced by the trade war, across a variety of product categories. According to NielsenIQ, products are broadly classified into 9 product departments. These include 1) Health & Beauty Care (cosmetics, personal care, medicines etc.), 2) Dry Grocery (food, soft drinks etc.), 3) Frozen Foods, 4) Diary Products (eggs, milk, cheese etc.), 5) Fresh Produce (deli, fresh vegetables, fruits etc.), 6) Meat, 7) Non-food Grocery (laundry products, paper products, pet care etc.), 8) Alcoholic Beverages, and 9) General Goods (appliances, cookware, automotive, toys etc.).

In 9 sub-samples, we regress the total spending against the variables $Treat$, $Post$, and their interaction term within a Difference-in-Differences framework. Each sub-sample includes product purchases from distinct product departments. It is important to highlight that the unit of observation in this table is at the Household - Product - Quarter level, which differs from the approach used in Table 2. The analysis utilizes a panel dataset, wherein each data point represents the spending on 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. We include both the household $\times$ product and time $\times$ product fixed effects. The variations in both $Treat$ and $Post$ are fully absorbed by the fixed effects.

Regression results are reported in Table 6. Our analysis reveals that the decline in consumer spending exhibits considerable variation across different product categories. The interaction term $Treat \times Post$ yields negative coefficients that are statistically significant at the 10 percent level or lower in four different specifications. When it comes to the consumption of daily essentials, such as dairy products, fresh produce, and meat, the impact is minimal. In contrast, the reduction in spending on durable items, including health and beauty products, dry groceries, and non-food grocery items, is notably more substantial. These results align with the theory suggesting that the consumption elasticity in response to wealth shocks is greater for durable goods.

6 Mechanism of the Consumption Response

6.1 The Labor Market and Income Shock

Our analysis so far suggests that the trade war has a negative impact on consumption, primarily driven by demand contraction. To further understand the mechanisms behind this demand contraction, we examine the trade war's effects on the labor market in Table 7. Specifically, we hypothesize that the trade war reduces wages, thereby constraining household consumption.

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

In Table 7, we present the DiD estimates for wages and employment. Treatment group counties exhibit weekly wage incomes \$10.26 lower than control group counties, representing approximately 1.4% of the sample mean (\$746). The year-on-year growth rate of weekly wages in treatment counties is 1.23% lower than in control counties post-trade war. Similarly, when measured as the relative change to the pre-trade war average, weekly wages in treatment counties are 1.96% lower. The trade war also reduces aggregate employment in treatment counties by 366 employees relative to control counties, though this difference is not statistically significant. This aligns with the slower adjustment of employment compared to wages due to labor market stickiness. When including time fixed effects, the results remain quantitatively similar. Overall, these findings support our hypothesis that the trade war negatively impacts the labor market, reducing wages and, in turn, household consumption.

We further examine the trade war's impacts on labor markets in the tradeable and non-tradeable sectors separately in Table 8. Since the tradeable sector is more directly exposed to international trade than the nontradeable sector (Autor, Dorn, and Hanson, 2013), we expect differential effects. For each county, we calculate employment and wages separately for tradeable and nontradeable sectors.

In Columns (1), (3), (5), and (7), we control for *County* and *Time* fixed effects. In Columns (2), (4), (6), and (8), we include $County \times Time$ fixed effects to compare wage and employment outcomes between tradeable and nontradeable sectors within the same county. The $County \times Time$ fixed effects models reveal that, relative to the nontradeable sector, the tradeable sector loses 549 more jobs. Wages in the tradeable sector are \$11 lower post-trade war, and wage growth is 0.2% slower (though statistically insignificant). Measured as the relative change to the pre-trade war average, tradeable sector wages are 2.1% lower than those in the nontradeable sector. These results demonstrate that the tradeable sector, which is directly exposed to the trade war, experiences larger declines in employment and wages.

6.2 Vertical Integration within the Same Industry

Finally, we explain why import tariffs on Chinese products fail to protect local industries and instead harm the economy. Prior work on the "China Shock" finds that import competition from China harms the U.S. labor market and workers' welfare (Autor, Dorn, and Hanson, 2013; Cen, Fos, and Jiang, 2023). While the trade war aimed to shield U.S. industries, our empirical results suggest the opposite.

As Wang et al. (2018) argue, this may stem from the intertwined nature of U.S. and Chinese industries, which are not only competitive but also complementary. Earlier studies, such as Autor, Dorn, and Hanson (2013), find a negative impact from Chinese imports between 1990 and 2007, when Chinese imports primarily acted as competitors. However, the composition of U.S. imports from China has since shifted significantly, reflecting growing supply-chain dependencies.

Figure A.3 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 capital and intermediate goods have grown. 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 shifted to 31.8%, 38.8%, and 27.5%, respectively, reflecting a significant increase in capital and intermediate goods. The bottom panel of Figure A.3 shows China's market share in U.S. imports by category. In 2001, 26% of U.S. consumption goods were imported from China, peaking at 37% in 2010 before declining. In contrast, China's share of U.S. capital goods imports rose from 10.0% in 2001 to 39.4% in 2017, while intermediate goods increased from 4.6% to 14.1%. These trends highlight the growing reliance of U.S. firms on Chinese supply chains. Imports from China are no longer limited to competitors or substitutes. The rising share of capital and intermediate goods reflects deepening supply-chain dependencies, making tariffs costlier for U.S. firms.

Given these dynamics, tariffs imposed on a domestic firm's own industry may not protect them from competition but instead backfire. Two mechanisms explain this outcome. First, many U.S. firms (e.g., in electronics and apparel) outsourced production to China under Original Equipment Manufacturer (OEM) or Original Design Manufacturer (ODM) models, retaining design and branding. Higher tariffs on imports from their own industries increase costs for these firms that offshore production.

Second, even within industries, labor division and supply-chain interdependence persist. For example, the pharmaceutical industry imports key starting materials and Active Pharmaceutical Ingredients (APIs) from China. Protective tariffs raise costs for firms reliant on Chinese inputs [12].

Therefore, when an industry faces increased import tariffs, the effects on firms within the industry are heterogeneous: protective tariffs may benefit firms competing directly with Chinese imports, but they simultaneously raise costs for firms that offshore production to China or rely on Chinese inputs. U.S. firms with strong bargaining power may pass these costs to Chinese partners, while weaker firms absorb them, leading to reduced competitiveness. This forces firms to reduce wages, cut jobs, or delay hiring, amplifying labor market pressures. Our empirical evidence of reduced consumption caused by the trade war suggests that the negative supply-chain effects dominate the limited protective benefits.

Therefore, we conjecture that the reduction in consumption post-trade war is primarily driven by counties reliant on Chinese supply chains. To test this underlying mechanism, ideal data would identify firms vertically linked to Chinese supply chains and firms horizontally competing with Chinese imports within a county. However, due to data limitations, we conduct two indirect tests using industry-level measures to capture the trade war's heterogeneous impacts across industries. These tests aim to determine whether the supply-chain channel or the protective effect dominates when an industry faces tariff increases. First, we use employment-based measures to capture industry exposure to supply-chain disruptions

[12] Tariffs may also propagate through supply networks, affecting both downstream and upstream industries. These effects are not limited to manufacturing sectors. For example, tariffs on computers and printers could increase office work costs (Wang et al., 2018).

and competitive shocks. Second, we decompose tariffs by product type—capital goods, intermediate goods, and consumption goods—to isolate supply-chain cost shocks from import competition effects. The following sections present the results of these two tests separately.

6.2.1 Employment-Based Measures of Supply-Chain Integration and Import Competition

In the first test, we make assumptions about each industry's share of employment competing with Chinese imports and the share relying on Chinese imports. We use the 2017 Input-Output Accounts Data from the U.S. Bureau of Economic Analysis, which provides supply and use information for 402 6-digit NAICS industries. We aggregate this upstream and downstream information to the 3-digit NAICS level. For each industry, we calculate the percentage of inputs sourced from the same industry ($UpstreamWeight_s$) and the percentage of output consumed by the same industry ($DownstreamWeight_s$). A higher $UpstreamWeight_s$ indicates greater reliance on inputs from the same industry, and we assume that such industries have a higher proportion of their workforce reliant on inputs from China, suggesting that tariff increases are more likely to raise costs. Conversely, a higher $DownstreamWeight_s$ indicates that a larger share of output is consumed within the same industry, and we assume that such industries have more workers producing goods that compete with Chinese imports, suggesting potential benefits from tariffs. Figure A.2 provides detailed information on these upstream and downstream weights for each industry.

For each county c, we compute the proportion of workers in industries with high intra-industry input reliance ($EmpUpstream_c$) and output consumption ($EmpDownstream_c$), as defined in Equation 8 and Equation 9, respectively. $EmpUpstream_c$ and $EmpDownstream_c$ are employment-based measures that aim to capture whether a county is vertically integrated with Chinese supply chains or horizontally competing with imports from China.

$$EmpUpstream_c = \frac{\sum_{s \in TradeableSectors} Emp_s \times UpstreamWeight_s}{\sum_{s \in AllSectors} Emp_s} \tag{8}$$

$$EmpDownstream_c = \frac{\sum_{s \in TradeableSectors} Emp_s \times DownstreamWeight_s}{\sum_{s \in AllSectors} Emp_s} \tag{9}$$

We then define $Treat(EmpUpstream)$ and $Treat(EmpDownstream)$ as binary indicators based on whether a county's $EmpUpstream_c$ or $EmpDownstream_c$ exceeds the median value across treatment counties. Counties with $Treat(EmpUpstream) = 1$ have a larger proportion of workforces dependent on Chinese supply chains, while $Treat(EmpDownstream) = 1$ indicates counties with workforces more exposed to import competition.

In Table 9, we present results on the consumption of these counties. The regression specification is similar to that of Table 2, with the addition of two newly constructed dummy variables: $Treat(EmpUpstream)$ and $Treat(EmpDownstream)$. The negative coefficients on $Treat \times Post$ across all columns confirm reduced consumption in treatment counties post-trade war. However, the coefficients of $Treat(EmpUpstream) \times Post$ and $Treat(EmpDownstream) \times Post$ reveal opposing effects, highlighting the heterogeneous impacts of tariffs. The coefficients of $Treat(EmpUpstream) \times Post$ are negative and statistically significant, indicating that counties with greater reliance on intra-industry supply chains experience amplified consumption declines. For example, in Column (2), households in high-reliance counties spend \$18.9 less post-trade war than the average treatment group, suggesting their economic situation is significantly worse. Conversely, the coefficients of $Treat(EmpDownstream) \times Post$ are positive and statistically significant, implying that counties exposed to import competition experience meaningful mitigation effects after tariffs are raised. In Column (2), households in these counties spend \$17.8 more than the average treatment group. When combined with the coefficient of $Treat \times Post$, the net effect of the trade war for these households is even positive. Results using alternative dependent variables or specifications yield qualitatively similar patterns.

These findings underscore the heterogeneous effects of the trade war across counties. Our main results are primarily driven by counties whose supply chains are disrupted by increased tariffs, while counties benefiting from reduced import competition experience offsetting gains.

6.2.2 Product-Based Measures of Supply-Chain Integration and Import Competition

Our second test uses product-level classification to determine whether an industry is more vertically integrated with Chinese supply chains or more likely to compete directly with imports from China. We achieve this by categorizing imported goods as capital goods, intermediate goods, or consumption goods. Using each imported good's Harmonized System (HS) code, we map it to its corresponding Broad Economic Categories (BEC). We then link each BEC to its end-use classification in the System of National Accounts (SNA), allowing us to classify each imported good into one of the three categories: capital goods, intermediate goods, or consumption goods.

Aggregating this product-level information, we decompose industry-level imports and tariffs into these three categories. In Figure A.4, we show the breakdown of tariff increases for each industry, illustrating the percentage increase in tariffs for capital goods, intermediate goods, consumption goods, and unclassified goods. The figure reveals that even industries with similar overall tariff increases can exhibit stark differences in the composition of those increases. For example, while the Plastics, Fishing, and Computer industries all experienced a 10% increase in tariffs during the trade war, the drivers of these increases vary significantly. In the Fishing sector, the tariff increase is driven by higher tariffs on consumption goods. In the Plastics sector, the increase is primarily due to tariffs on intermediate goods. In the Computer sector, the increase is largely attributable to tariffs on capital goods.

By decomposing an industry's tariff increase into these three components, we aim to assess whether the increase harms the industry by raising costs through the supply chain or mitigates competition from China. Imported capital goods and intermediate goods could compete with U.S. firms that also produce these goods. However, due to data limitations, we cannot precisely determine how much of these imports serve as inputs for U.S. firms versus how much directly compete with locally produced capital and intermediate goods. Our assumption is that, compared to consumption goods, capital goods and intermediate goods are more likely to be complementary rather than substitutable with U.S. products. Therefore, if an industry's tariff increase is driven by capital goods or intermediate goods, it is more likely to face higher production costs. Conversely, if the increase is driven by consumption goods, the protective effect is assumed to be stronger.

Using each industry's capital goods tariffs, intermediate goods tariffs, and consumption goods tariffs, we calculate county-level tariffs for these three categories, following the methodology outlined in Equation 2 and Equation 4. We then define treatment counties using a similar approach and create three dummy variables: $Capital$, $Intermediate$, and $Consumption$. Specifically, $Capital$ equals one if a county's increase in capital goods tariffs exceeds the median increase across all counties. The variables $Intermediate$ and $Consumption$ are defined analogously for intermediate goods and consumption goods tariffs, respectively. These dummies 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 discussed earlier, we assume that tariff increases on capital goods and intermediate goods are more likely to harm local firms by raising costs, while tariff increases on consumption goods are more likely to mitigate import competition from China.

In Table 10, we present results on consumption across counties using a specification similar to our baseline results in Table 2. 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 $Treat \times Post \times Consumption$. We find that the coefficients on $Treat \times Post \times Capital$ and $Treat \times Post \times Intermediate$ are negative but statistically insignificant, suggesting that counties with large increases in capital or intermediate goods tariffs reduce consumption by a magnitude similar to the average treatment group.

In contrast, the coefficients on $Treat \times Post \times Consumption$ in Columns (5) and (6) are significantly positive, indicating that households in counties with consumption goods tariff increases fare relatively better than 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 results again suggest that our main results are mainly driven by counties with tariff increases in capital goods and intermediate goods.

In conclusion, our results from the two tests indicate that the trade war's reduction in consumption stems primarily from tariff-induced increases in input costs. The negative cost shock to firms is transmitted to the labor market, and the resulting adjustments in wages ultimately affect consumer spending. While protective import tariffs may offer some shelter for certain local industries, their positive effect on consumption is modest at best. This aligns with Wang et al. (2018), who argue that U.S.-China trade relations are characterized more by supply-chain complementarity than direct competition. Consequently, tariffs have limited success in stimulating local production to substitute imports but pose significant risks of supply-chain disruption.

7 Conclusion

In this paper, our examination delves into the repercussions of the trade war on U.S. households, with a specific focus on the import tariffs imposed on Chinese goods, intended to shield U.S. domestic industries. Contrary to anticipated benefits, our investigation uncovers a scenario where households in counties experiencing substantial increases in import tariffs exhibit lower aggregate consumption. Detailed analysis at the product level emphasizes that this spending reduction reflects a contraction in demand. Notably, our finding that counties facing larger import tariff hikes also have lower wages aligns with this conjecture. The underlying cause for the diminished consumption and wages appears to be the dominance of adverse effects stemming from disrupted supply chains over the intended benefits of tariff protection for local firms. Our study sheds light on the dynamics of trade relations between the U.S. and China, suggesting that heightened import tariffs might not necessarily fortify local industries but can instead disrupt supply chains, contributing to unfavorable outcomes in the labor market.

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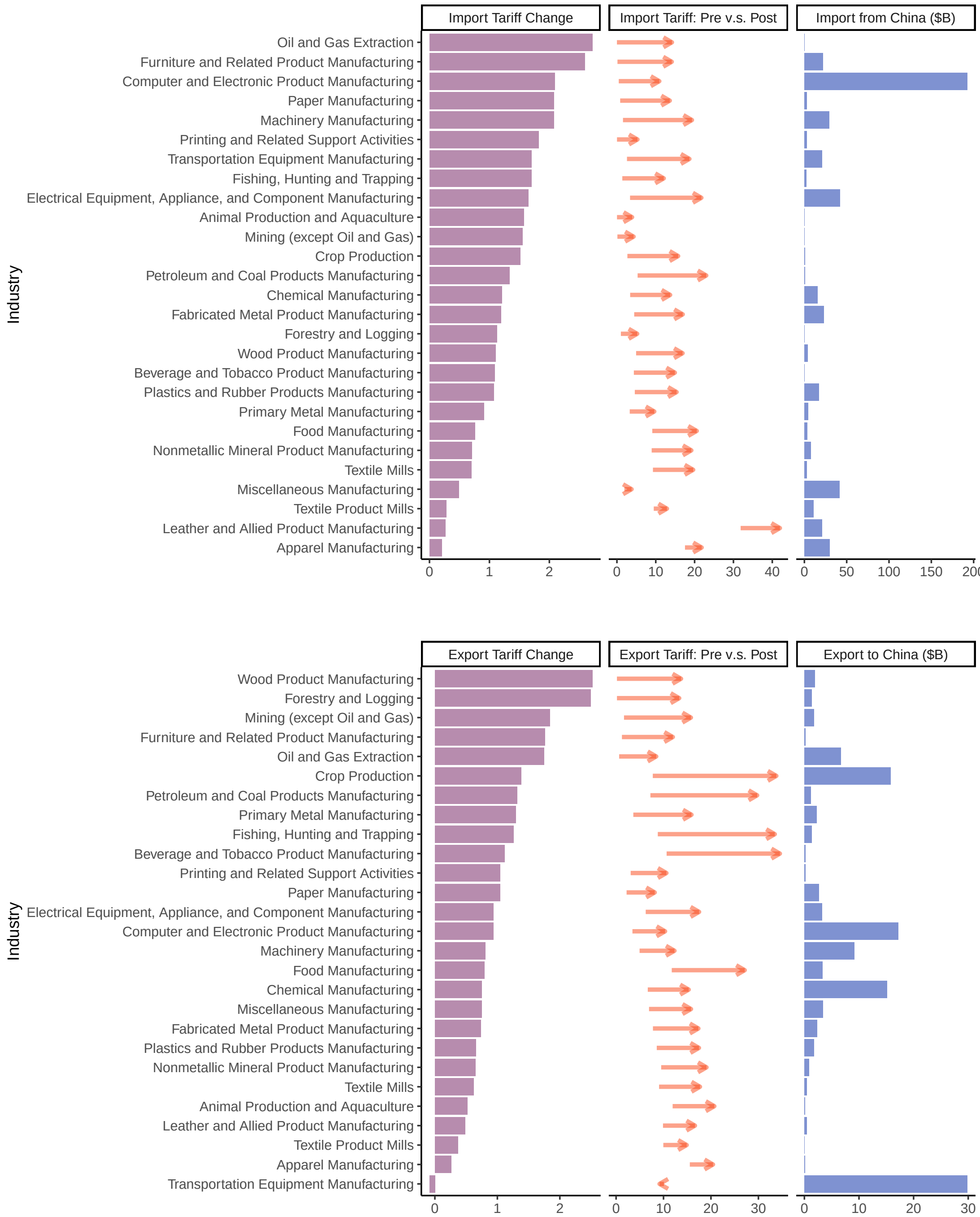
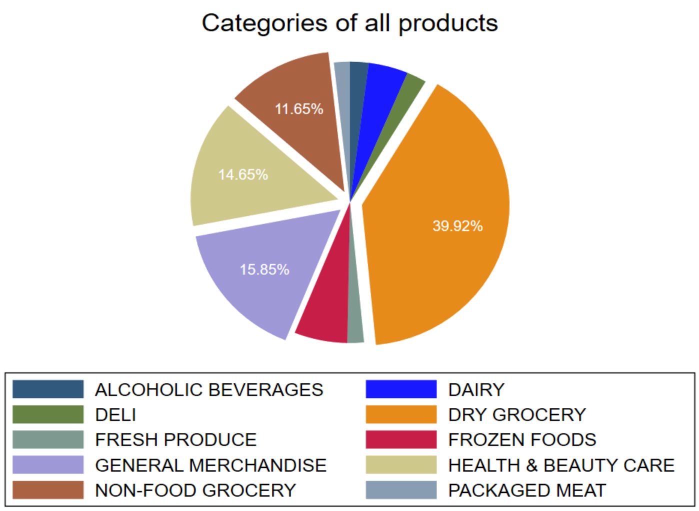
Figure 1. Changes in Tariff Rates, by Industry



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.

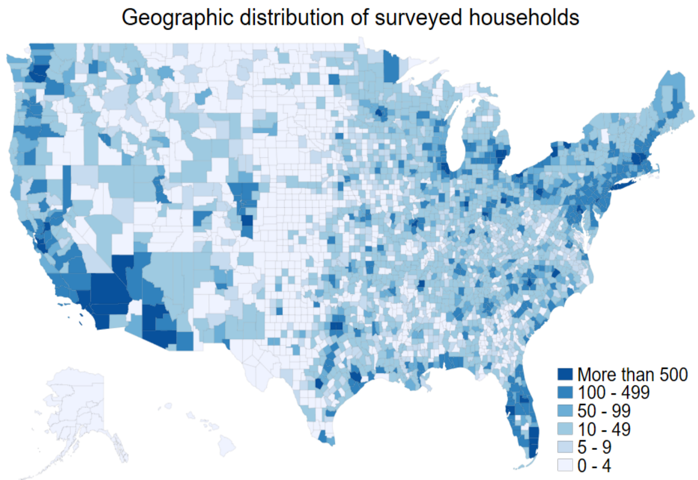
Figure 2. Categories of Household Consumption



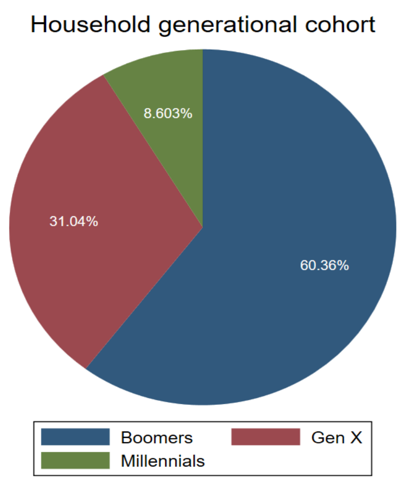
This figure presents the percentages of product purchases by their corresponding product categories.

Figure 3. Distribution of Households

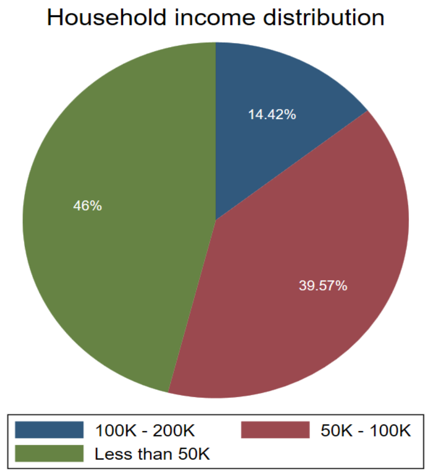
(a) By Location



(b) By Age

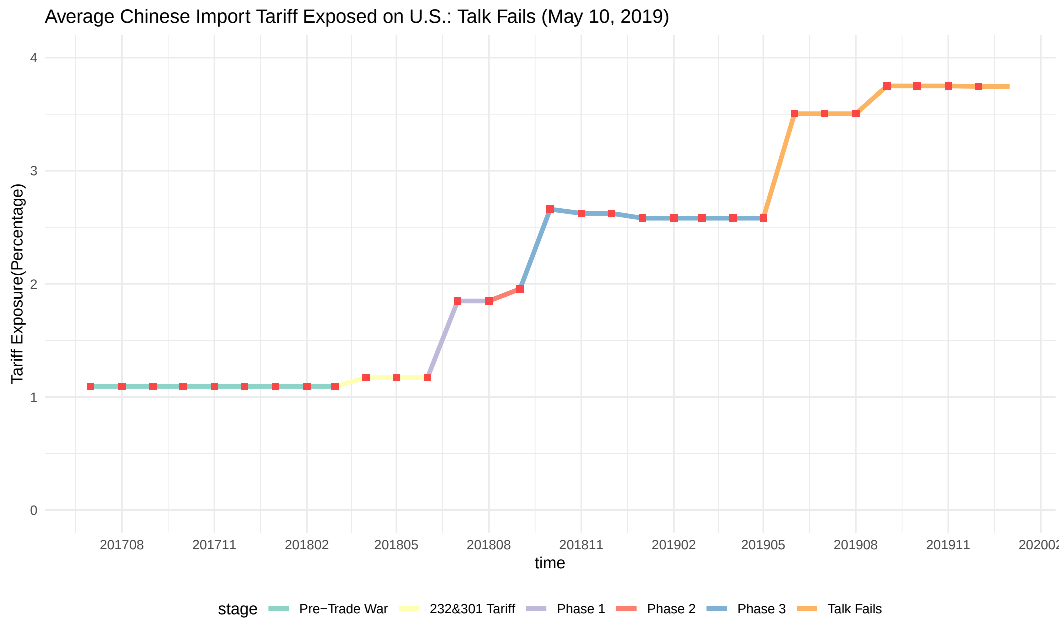


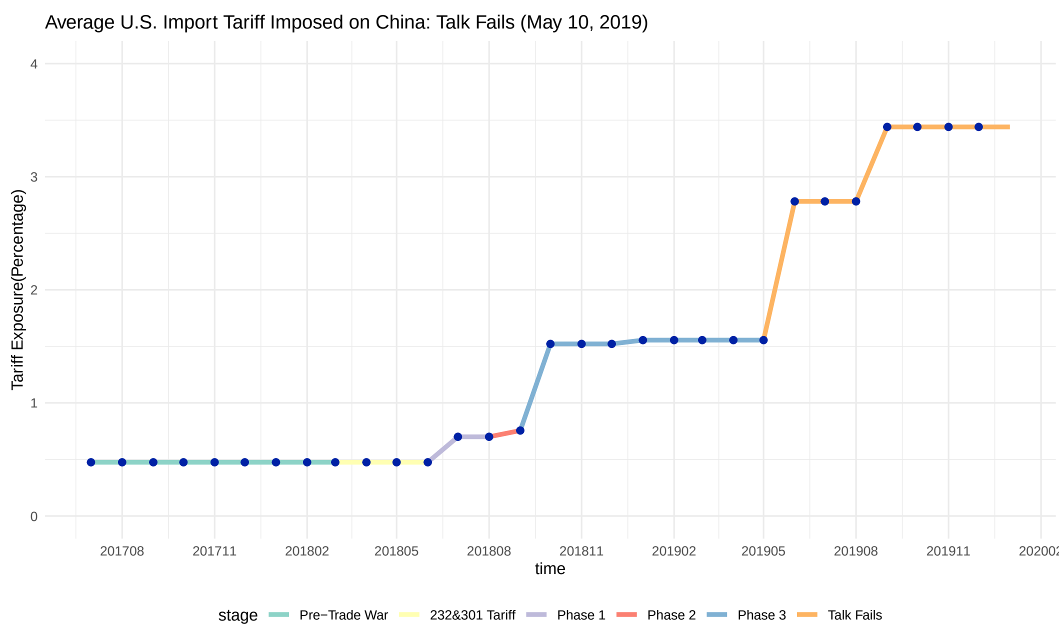
(c) By Income



The figures plot the distribution of the surveyed households by location, age and income. In figure (a), areas of the heat map filled with darker blue are populated with higher number of surveyed households. Figure (b) shows the distribution of the surveyed households by the average of the ages of household heads. The Boomer Generation is defined as the group born before 1964. Generation X includes the group born after 1964 but before 1980. Millennial Generation includes the group born after 1980 but before 1994. Figure (c) shows the distribution of the surveyed households by household income, across the groups with less than 50K, between 50K and 100K, and above 100K, respectively.

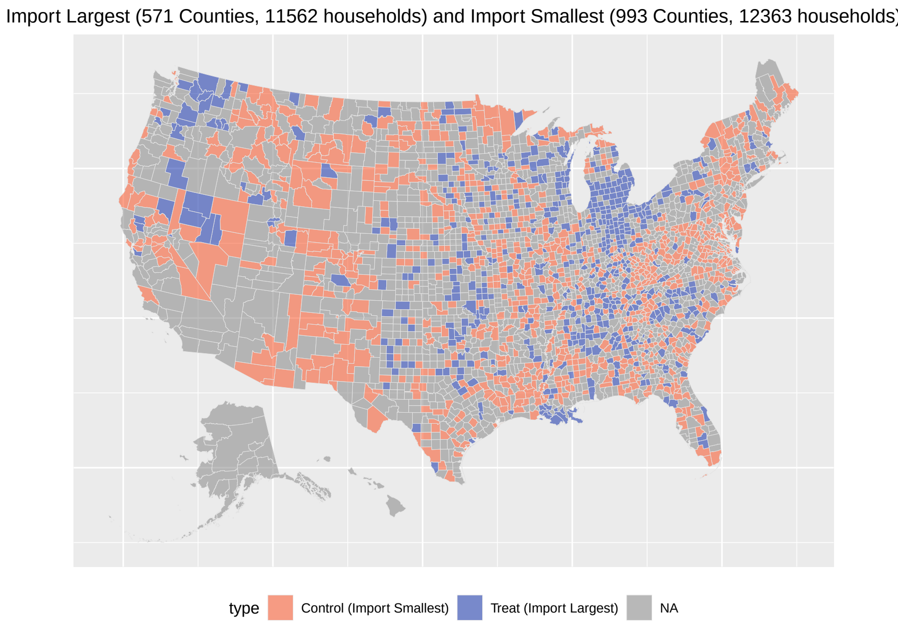
Figure 4. Timeline of the United States - China Trade War





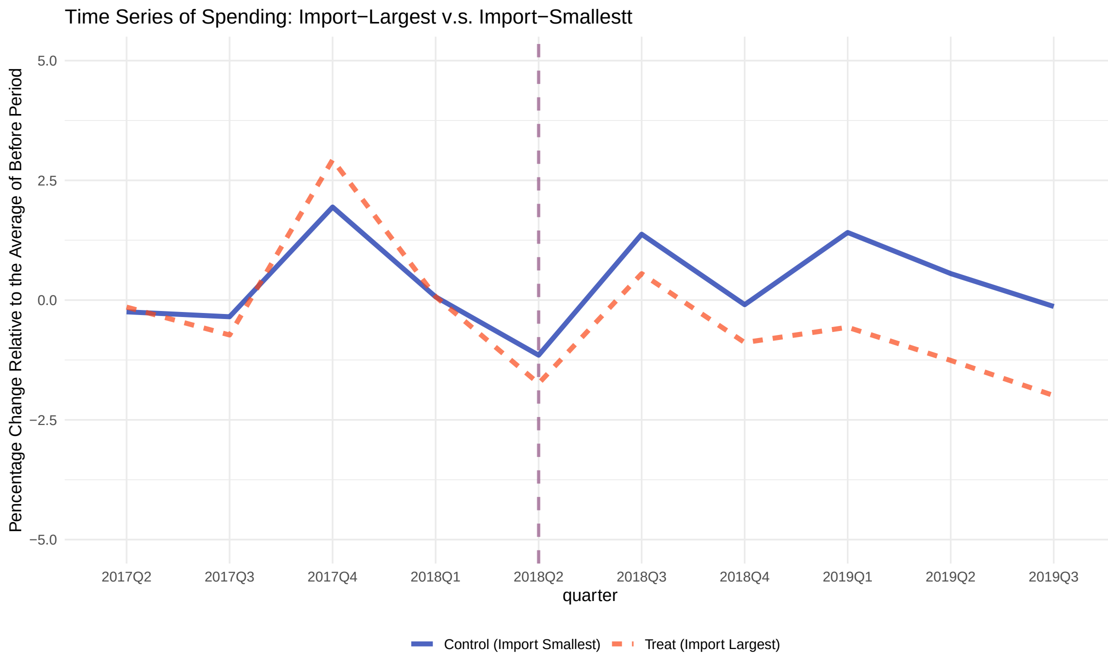
The figures plot the time-series variations in the level of export and import tariff exposure across the United States. We first calculate the employment-based tariff exposure at the county level, and then plot the average of all counties on the vertical axis. Figure (a) presents the variations in average tariff exposure of the goods imported from China by the United States. Figure (b) shows the variations in average tariff exposure of the goods exported to China by the United States. We highlight the tariff exposures in different stages of the trade war using different colors.

Figure 5. Geographic Distribution of Treatment and Control Counties



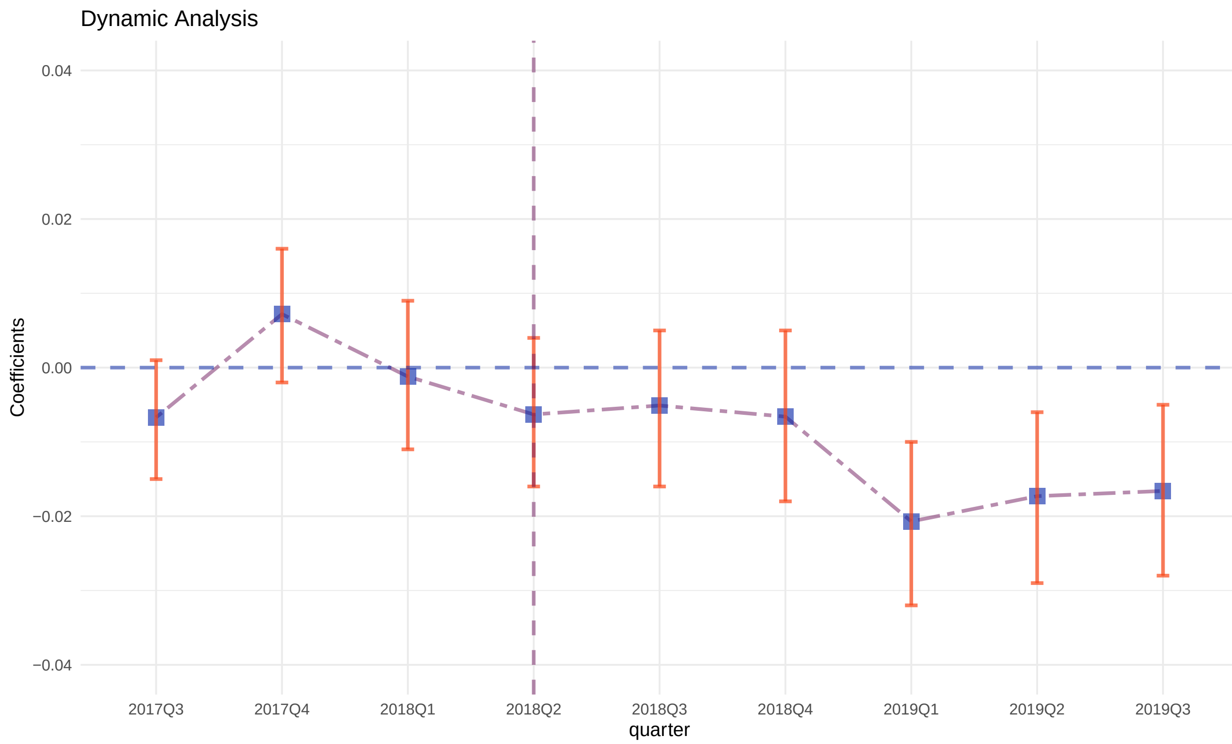
The figure visualizes the distribution of the treatment and control counties across the United States.

Figure 6. Time-series Changes in Household Spending



The figure presents the time-series mean of the households' quarterly spending, from Q3 of 2017 to Q3 of 2019. The red line plots the mean of the households' spending in the treatment group. The blue line plots the mean of the households' spending in the control group.

Figure 7. Dynamic Analysis



The figure presents the coefficient estimates and their corresponding 10% confidence intervals of the interaction terms in the Difference-in-Differences (DiD) regression. The regression model is specified in Section 5.1.

Table 1. Summary Statistics

This table reports the summary of statistics for the key variables. The level of observation of *Quarterly Spending* is on the household-quarter level, while that of the other variables is on the county level. The number of observations, mean, median, min, max, and standard deviation are reported. Panel A reports the variable statistics in the treatment group, and Panel B reports the variable statistics in the control group. Detailed variable definitions are available in Appendix Table A.1.

Panel A: Treatment Group (Import-Most)	N	mean	p50	min	max	sd
Quarterly Spending	102,791	1,345	1,171	183.4	4,187	805.2
Post-TW Emp-Adjusted Import Tariff	571	3.636	3.223	0.395	13.57	1.887
Pre-TW Emp-Adjusted Import Tariff	571	0.794	0.683	0	3.524	0.520
Import Exposure	571	0.909	0.889	0.329	2.142	0.212
Export Exposure	571	0.563	0.483	-0.0282	2.087	0.341

Panel B: Control Group (Import-Least)	N	mean	p50	min	max	sd
Quarterly Spending	109,741	1,341	1,171	183.4	4,187	804.9
Post-TW Emp-Adjusted Import Tariff	993	0.649	0.490	0	5.926	0.723
Pre-TW Emp-Adjusted Import Tariff	993	0.225	0.119	0	4.042	0.353
Import Exposure	993	0.251	0.269	0	0.583	0.181
Export Exposure	993	0.357	0.385	0	1.217	0.239

Table 2. Baseline Regression

In this table, we regress the quarterly household spending on the *Treat*, *Post* and the interaction term in a Difference-in-Differences setting. Each observation is the total spending of a household (i) in quarter (t). *Quarterly Spending* is the total dollar value spent by a household tracked by Nielsen IQ. *Treat* is a dummy variable that turns on when the household is in the treatment group. We only include the quarterly observations from Q2 2017 to Q3 2019. The *Post* is a dummy variable that equals one for every quarter t that falls between Q3 2018 and Q3 2019, and equals zero for every quarter t observed on or before 2018 Q2. In column 1, 3 and 5, we include the household FEs. In column 2, 4 and 6, we include both the household and quarter fixed effects that absorb the variations in both *Treat* and *Post*. The dependent variables are *Quarterly Spending* (columns 1 and 2), *Ln(Spending)* (columns 3 and 4), and the *Pct Change* in total spending (columns 5 and 6), respectively. 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.

	(1)	(2)	(3)	(4)	(5)	(6)
	Quarterly Spending	Quarterly Spending	Ln (Spending)	Ln (Spending)	Pct Change	Pct Change
Treat × Post	-14.0564***	-13.9642***	-0.0111***	-0.0110***	-1.2282***	-1.2242***
	(-2.93)	(-2.91)	(-2.87)	(-2.85)	(-3.54)	(-3.53)
Post	-35.9696***		-0.0361***		-0.1512	
	(-10.61)		(-13.19)		(-0.61)	
Observations	212,532	212,532	212,532	212,532	212,532	212,532
Adjusted R-squared	0.791	0.792	0.768	0.769	0.131	0.133
Household FE	Y	Y	Y	Y	Y	Y
Time FE	N	Y	N	Y	N	Y

Table 3. Decomposing the Demand and Supply Effects

In this table, we regress the spending, price and quantity sold for both the treated and control products 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, wherein each data point represents the spending, price, and quantity 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 Q2 2017 to Q3 2019. The *Post* is a dummy variable that equals one for every quarter t that falls between Q3 2018 and Q3 2019, and equals zero for every quarter t observed on or before 2018 Q2. 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 *Spending* (columns 1 and 2), *Quantity* (columns 3 and 4), and the *Price* (columns 5 and 6), respectively. In Panel A, *Spending* and *Quantity* equals zero if the household didn't make any purchase of the product in that particular quarter - and in this case, we assign the value of *Price* as the same product's average price paid by other households in the same county (if available). In Panel B, we only include the household - product - quarters where the household's spending on a product is non-zero. 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) Spending	(2) Spending	(3) Quantity	(4) Quantity	(5) Price	(6) Price
Treat × Post	-0.0074**	-0.0075**	-0.0023**	-0.0023**	-0.0060***	-0.0063***
	(-2.31)	(-2.35)	(-2.39)	(-2.41)	(-7.34)	(-6.81)
Observations	232,875,167	232,875,167	232,875,167	232,875,167	78,322,449	68,070,803
Adjusted R-squared	0.184	0.397	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) Spending	(2) Spending	(3) Quantity	(4) Quantity	(5) Price	(6) Price
Treat × Post	-0.0133*	-0.0386***	-0.0006	-0.0080**	-0.0053***	-0.0058***
	(-1.91)	(-3.08)	(-0.26)	(-2.18)	(-3.67)	(-2.65)
Observations	37,662,290	18,960,788	37,662,290	18,960,788	37,662,290	18,960,788
Adjusted R-squared	0.538	0.711	0.199	0.553	0.889	0.912
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 4. Robustness Check

This table presents robustness checks using alternative specifications. We extend the analysis to include all counties in the Nielsen data sample and incorporate export tariffs for each county. Panel A reports on household quarterly spending, similar to Table 2. Panels B and C replicate the analysis from Table 3, with dependent variables being Household-Product-Quarter spending, price, and quantity. The sample includes quarterly observations from 2017Q2 to 2019Q3. $ImportTariff$ and $ExportTariff$ are defined as contemporaneous county-quarter tariffs, as outlined in Equation 2. We use the same set of fixed effects as in Table 2 and Table 3. In Panel B, *Spending* and *Quantity* are set to zero for households with no product purchases in a given quarter. In these cases, *Price* is assigned as the average price paid by other households for the same product in the same county (if available). Panel C includes only those Household-Product-Quarter observations where the household's spending on a product is non-zero. 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: Household Quarterly Spending

	(1) Quarterly Spending	(2) Quarterly Spending	(3) Ln (Spending)	(4) Ln (Spending)	(5) Pct Change	(6) Pct Change
log(1+Import Tariff)	-55.8475***	-23.3429***	-0.0457***	-0.0199***	-2.2986***	-2.0745***
	(-10.16)	(-3.36)	(-10.31)	(-3.55)	(-5.84)	(-4.16)
log(1+Export Tariff)	-29.6058***	-0.8473	-0.0378***	0.0002	0.2579	0.0702
	(-3.97)	(-0.10)	(-6.29)	(0.03)	(0.48)	(0.11)
Observations	596,428	596,428	596,428	596,428	569,804	569,804
Adjusted R-squared	0.795	0.795	0.770	0.770	0.102	0.103
Household FE	Y	Y	Y	Y	Y	Y
Time FE	N	Y	N	Y	N	Y

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

	(1) Spending	(2) Spending	(3) Quantity	(4) Quantity	(5) Price	(6) Price
log(1+Import Tariff)	-0.0120***	-0.0130***	-0.0032**	-0.0033**	-0.0111***	-0.0114***
	(-2.60)	(-2.83)	(-2.33)	(-2.39)	(-9.07)	(-8.26)
log(1+Export Tariff)	0.0071	0.0071	0.0023	0.0024	-0.0031*	-0.0026
	(1.24)	(1.24)	(1.36)	(1.44)	(-1.89)	(-1.40)
Observations	606,201,218	606,201,218	606,201,218	606,201,218	241,316,368	215,501,744
Adjusted R-squared	0.190	0.401	0.098	0.350	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) Spending	(2) Spending	(3) Quantity	(4) Quantity	(5) Price	(6) Price
log(1+Import Tariff)	-0.0262**	-0.0565***	-0.0014	-0.0107**	-0.0087***	-0.0092***
	(-2.54)	(-3.14)	(-0.44)	(-2.02)	(-4.23)	(-2.98)
log(1+Export Tariff)	-0.0027	0.0117	-0.0014	-0.0004	-0.0018	-0.0022
	(-0.22)	(0.54)	(-0.38)	(-0.07)	(-0.73)	(-0.60)
Observations	104,529,006	51,260,642	104,529,006	51,260,642	104,529,006	51,260,642
Adjusted R-squared	0.544	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 5. The Heterogeneity across Households

In this table, we regress the quarterly household spending on the *Treat*, *Post* and the interaction term in a Difference-in-Differences setting. The analysis is based on a panel data set, where each observation is the total spending of a household (i) in quarter (t). *Quarterly Spending* is the total dollar value spent by a household tracked by Nielsen IQ. *Treat* is a dummy variable that turns on when the household is in the treatment group. We only include the quarterly observations from Q2 2017 to Q3 2019. The *Post* is a dummy variable that equals one for every quarter t that falls between Q3 2018 and Q3 2019, and equals zero for every quarter t observed on or before 2018 Q2. We conduct a few sub-sample analysis based on the household's income (Panel A) and age (Panel B). In Panel A, we divide the households into those making less than 30K, between 30K and 50K, between 50K and 100K, and above 100K annually, respectively. In Panel B, we divide the households into the Boomers Generation, Generation X, and the Millennials, respectively. In columns 1, 3, 5 and 7 (available in Panel A only), we include the household FEs. In columns 2, 4, 6 and 8 (available in Panel A only), we include both the household and quarter fixed effects that absorb the variations in both *Treat* and *Post*. 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	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent Variable: Pct Change							
	<30k		30k-50k		50k-100k		>100k	
Treat × Post	-0.3583	-0.3759	-1.7154**	-1.7219**	-0.9700*	-0.9614*	-1.9422**	-1.9171**
	(-0.44)	(-0.46)	(-2.42)	(-2.42)	(-1.79)	(-1.77)	(-2.37)	(-2.34)
Post	0.0514		-0.3881		-0.5269		0.6885	
	(0.09)		(-0.77)		(-1.35)		(1.20)	
Observations	41,967	41,967	49,672	49,672	82,918	82,918	37,975	37,975
Adjusted R-squared	0.137	0.138	0.137	0.139	0.128	0.130	0.121	0.124
Household FE	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	N	Y	N	Y	N	Y	N	Y

Panel B	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable: Pct Change					
	Generation M		Generation X		Generation B	
Treat × Post	-1.6659	-1.6797	-1.5005**	-1.4825**	-0.8568*	-0.8554*
	(-1.27)	(-1.29)	(-2.08)	(-2.06)	(-1.82)	(-1.82)
Post	-4.2905***		-1.4339***		1.3415***	
	(-4.52)		(-2.76)		(4.00)	
Observations	19,263	19,263	57,731	57,731	107,249	107,249
Adjusted R-squared	0.151	0.160	0.143	0.147	0.124	0.127
Household FE	Y	Y	Y	Y	Y	Y
Time FE	N	Y	N	Y	N	Y

Table 6. The Heterogeneity across Consumption Groups

The analysis involves regressing the total spending against the variables *Treat*, *Post*, and their interaction term within a Difference-in-Differences framework. Each sub-sample includes product purchases from distinct product departments. It is important to highlight that the unit of observation in this table is at the Household - Product - Quarter level, which differs from the approach used in Table 2. The analysis utilizes a panel dataset, wherein each data point represents the spending on 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 Q2 2017 to Q3 2019. The *Post* is a dummy variable that equals one for every quarter t that falls between Q3 2018 and Q3 2019, and equals zero for every quarter t observed on or before 2018 Q2. 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. 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.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
					Spending				
Department	Frozen Food	Diary Products	Fresh Produce	Meat	Health & Beauty	Dry Grocery	Non-food	Alcoholic	General Goods
Treat × Post	-0.0060	0.0044	-0.0094	-0.0044	-0.0462*	-0.0401***	-0.0398**	-0.3609**	0.0354
	(-0.37)	(0.32)	(-1.48)	(-0.09)	(-1.81)	(-3.52)	(-1.99)	(-2.14)	(1.17)
Observations	3,331,401	3,014,699	20,032,356	422,802	3,005,780	21,345,936	3,663,301	225,997	1,430,272
Household × Product FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time × Product FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Adjusted R-squared	0.117	0.114	0.207	0.111	0.126	0.337	0.143	0.138	0.166

Table 7. The Impact on the Labor Market and Household Wage

This table presents regression results for various labor market outcomes in a Difference-in-differences framework, where we regress outcomes on $Treat$, $Post$, and their interaction term. The analysis uses county-quarter level panel data. Employment is aggregated across sectors for each county, and wages are calculated as an employment-weighted average. $Treat$ is a dummy variable indicating whether a county belongs to the treatment group. $Post$ is a dummy variable equal to one for quarters between Q3 2018 and Q3 2019, and zero for quarters on or before Q2 2018. Columns (1), (3), (5), and (7) include county fixed effects (FEs). Columns (2), (4), (6), and (8) add quarter FEs, which absorb variation in both $Treat$ and $Post$. Standard errors are clustered at the county 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.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Employment		Wage		Wage Growth (YoY)		Wage % Chg	
Treat × Post	-365.8769	-365.3584	-10.2631***	-10.2650***	-1.1287**	-1.1291**	-1.9646***	-1.9645***
	(-1.64)	(-1.64)	(-3.92)	(-3.92)	(-2.55)	(-2.55)	(-5.84)	(-5.83)
Post	-805.1372***		40.2238***		1.9053***		6.0735***	
	(-4.86)		(28.01)		(5.49)		(25.55)	
Observations	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	0.108	0.119	0.140	0.258
County FE	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	N	Y	N	Y	N	Y	N	Y

Table 8. The Impact on the Labor Market and Household Wage: Tradeable Sectors v.s. Non-Tradeable Sectors
This table examines the trade war's impact on labor markets in the tradeable and nontradeable sectors separately. Unlike Table 7, which aggregates data across sectors, this table calculates wages and employment separately for tradeable and nontradeable sectors within each county-quarter. Employment is aggregated within tradeable or non-tradeable sectors, and wages are computed as employment-weighted averages for tradeable or non-tradeable sectors. $Treat$ and $Post$ are defined as in Table 7. $Tradeable$ is a dummy variable equal to one if the observation corresponds to the tradeable sector of a county. Columns (1), (3), (5), and (7) include county and time fixed effects (FEs). Columns (2), (4), (6), and (8) control for $County \times Time$ FEs. 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.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Employment		Wage		Wage Growth(YoY)		Wage%Chg	
Treat× Post× Tradeable	-371.316*	-548.719**	-13.029**	-11.289*	-0.002	-0.002	-2.278***	-2.148***
	(-1.67)	(-2.06)	(-2.30)	(-1.95)	(-0.25)	(-0.29)	(-3.69)	(-3.59)
Treat× Post	-88.052		-1.083		-0.004		-0.402	
	(-0.43)		(-0.43)		(-0.78)		(-1.13)	
Treat× Tradeable	2,743.712	3,120.226	157.813***	157.904***	-0.021***	-0.021***	0.061	-0.020
	(0.62)	(0.70)	(12.05)	(12.06)	(-3.91)	(-4.04)	(0.72)	(-0.61)
Post× Tradeable	889.015***	1,057.477***	-11.999***	-14.387***	-0.018***	-0.018***	-1.576***	-1.737***
	(4.62)	(4.44)	(-2.74)	(-3.20)	(-2.70)	(-2.96)	(-3.17)	(-3.63)
Tradeable	-23,936.842***	-24,359.887***	159.303***	160.129***	0.009**	0.009**	-0.042	0.017
	(-6.84)	(-6.83)	(19.16)	(19.18)	(2.14)	(2.28)	(-0.52)	(0.75)
Observations	29,815	28,380	29,815	28,380	29,517	27,792	29,761	28,272
Adjusted R-squared	0.543	0.136	0.709	0.553	0.059	0.018	0.155	0.161
County FE	Y	N	Y	N	Y	N	Y	N
Time FE	Y	N	Y	N	Y	N	Y	N
County*Time FE	N	Y	N	Y	N	Y	N	Y

Table 9. The Vertical Transmission of Trade Shocks

In this table, we regress the quarterly household spending on the *Treat*, *Post* and the interaction term in a Difference-in-Differences setting. The analysis is based on a balanced panel, where each observation is the total spending of a household (i) in quarter (t). *Quarterly Spending* is the total dollar value spent by a household tracked by Nielsen IQ. *Treat* is a dummy variable that turns on when the household is in the treatment group. $Treat(Upstream)$ is a dummy variable that turns on when two conditions are met: (1) *Treat* is set to one, and (2) the household being treated is located in a county where its industries' upstream import exposure exceeds the median level of all counties being treated. $Treat(Downstream)$ is a dummy variable that turns on when two conditions are met: (1) *Treat* is set to one, and (2) the household being treated is located in a county where its industries' downstream import exposure falls below the median level of all counties being treated. We only include the quarterly observations from Q2 2017 to Q3 2019. The *Post* is a dummy variable that equals one for every quarter t that falls between Q3 2018 and Q3 2019, and equals zero for every quarter t observed on or before 2018 Q2. In column 1, 3 and 5, we include the household FEs. In column 2, 4 and 6, we include both the household and quarter fixed effects that absorb the variations in both *Treat* and *Post*. Standard errors are clustered at the household level. The dependent variables are *QUarterly Spending* (columns 1 and 2), $Ln(Spending)$ (columns 3 and 4), and the *Pct Change* in total spending (columns 5 and 6), respectively. 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.

	(1)	(2)	(3)	(4)	(5)	(6)
	Quarterly Spending		Ln(Spending)		Pct Change	
Treat(EmpUpstream)× Post	-18.6196*	-18.8876*	-0.0170**	-0.0172**	-1.5449**	-1.5653**
	(-1.71)	(-1.73)	(-2.00)	(-2.02)	(-1.99)	(-2.02)
Treat(EmpDownstream)× Post	17.8634*	17.8395*	0.0173**	0.0173**	1.2967*	1.3001*
	(1.74)	(1.74)	(2.14)	(2.13)	(1.76)	(1.76)
Treat× Post	-15.1388***	-14.9602***	-0.0124***	-0.0123***	-1.2508***	-1.2421***
	(-2.76)	(-2.73)	(-2.81)	(-2.78)	(-3.16)	(-3.14)
Post	-35.9696***		-0.0361***		-0.1512	
	(-10.61)		(-13.19)		(-0.61)	
Observations	212,532	212,532	212,532	212,532	212,532	212,532
Adjusted R-squared	0.791	0.792	0.768	0.769	0.131	0.133
Household FE	Y	Y	Y	Y	Y	Y
Time FE	N	Y	N	Y	N	Y

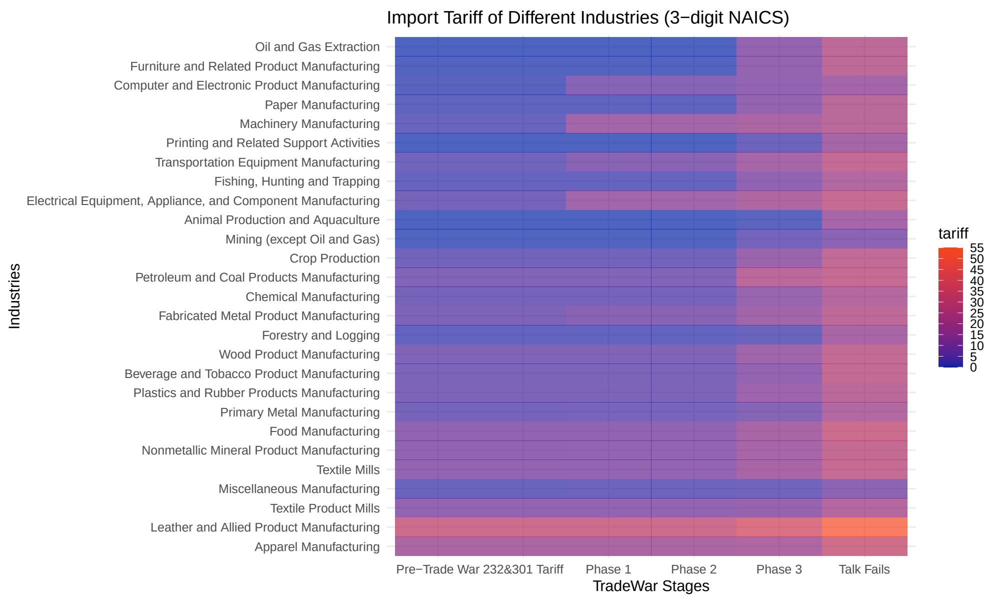
Table 10. The Decomposition of Tariff Increase

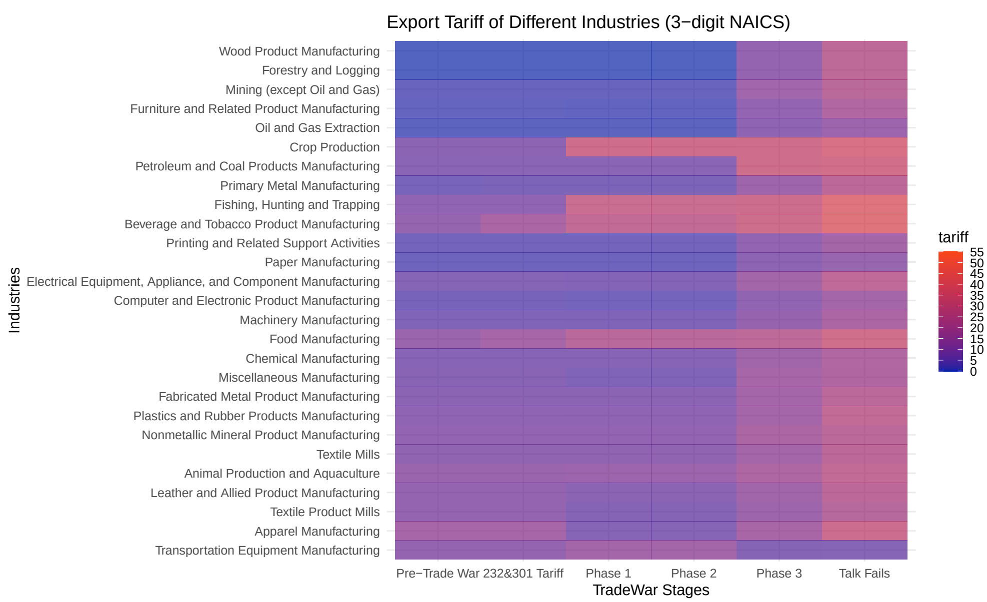
In this table, we regress the quarterly household spending on the *Treat*, *Post* and the interaction term in a Difference-in-Differences setting. The dependent variable is *Quarterly Spending* which is the total dollar value spent by a household tracked by Nielsen IQ. *Treat* and *Post* are defined the same as before. *Capital* is a dummy variable equal to 1 if a county's capital goods tariff increase is above the median of all sample counties. *Interdemidate* and *Consumption* are defined similarly. 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.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent Variable: Quarterly Spending							
Treat× Post× Capital	-12.3180	-11.8417					-14.2412	-13.7712
	(-0.44)	(-0.42)					(-0.50)	(-0.49)
Treat× Post × Intermediate			-9.7989	-9.0433			-19.6917	-18.8644
			(-0.29)	(-0.27)			(-0.57)	(-0.55)
Treat× Post × Consumption					22.7980**	22.7756**	25.1083**	25.0347**
					(2.16)	(2.15)	(2.33)	(2.32)
Post× Capital	12.2492*	12.1976*					14.9269**	14.8838**
	(1.69)	(1.68)					(2.03)	(2.02)
Post× Intermediate			-11.1901	-11.2418			-10.6409	-10.6805
			(-1.30)	(-1.31)			(-1.21)	(-1.21)
Post× Consumption					-11.2331	-11.2780	-11.8489	-11.8827
					(-1.58)	(-1.59)	(-1.63)	(-1.63)
Post× Treat	-5.5080	-5.8683	4.5245	3.9141	-26.6253***	-26.5000***	9.4494	8.3765
	(-0.20)	(-0.21)	(0.14)	(0.12)	(-3.34)	(-3.32)	(0.22)	(0.20)
Post	-44.4505***		-33.8901***		-31.8870***		-40.0206***	
	(-7.46)		(-8.98)		(-7.57)		(-6.38)	
Observations	212,532	212,532	212,532	212,532	212,532	212,532	212,532	212,532
Adjusted R-squared	0.791	0.792	0.791	0.792	0.791	0.792	0.791	0.792
Household FE	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	N	Y	N	Y	N	Y	N	Y

Appendix

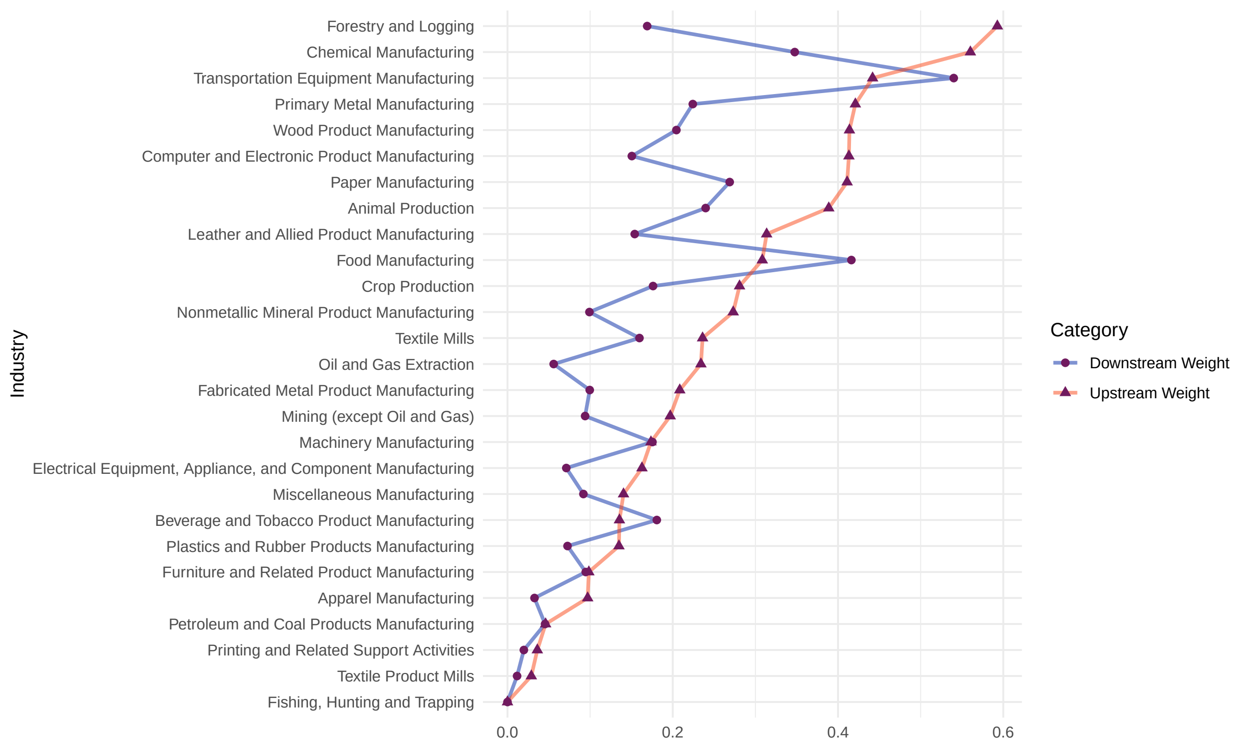
Figure A.1. Evolution of the Export and Import Tariff, by Industry





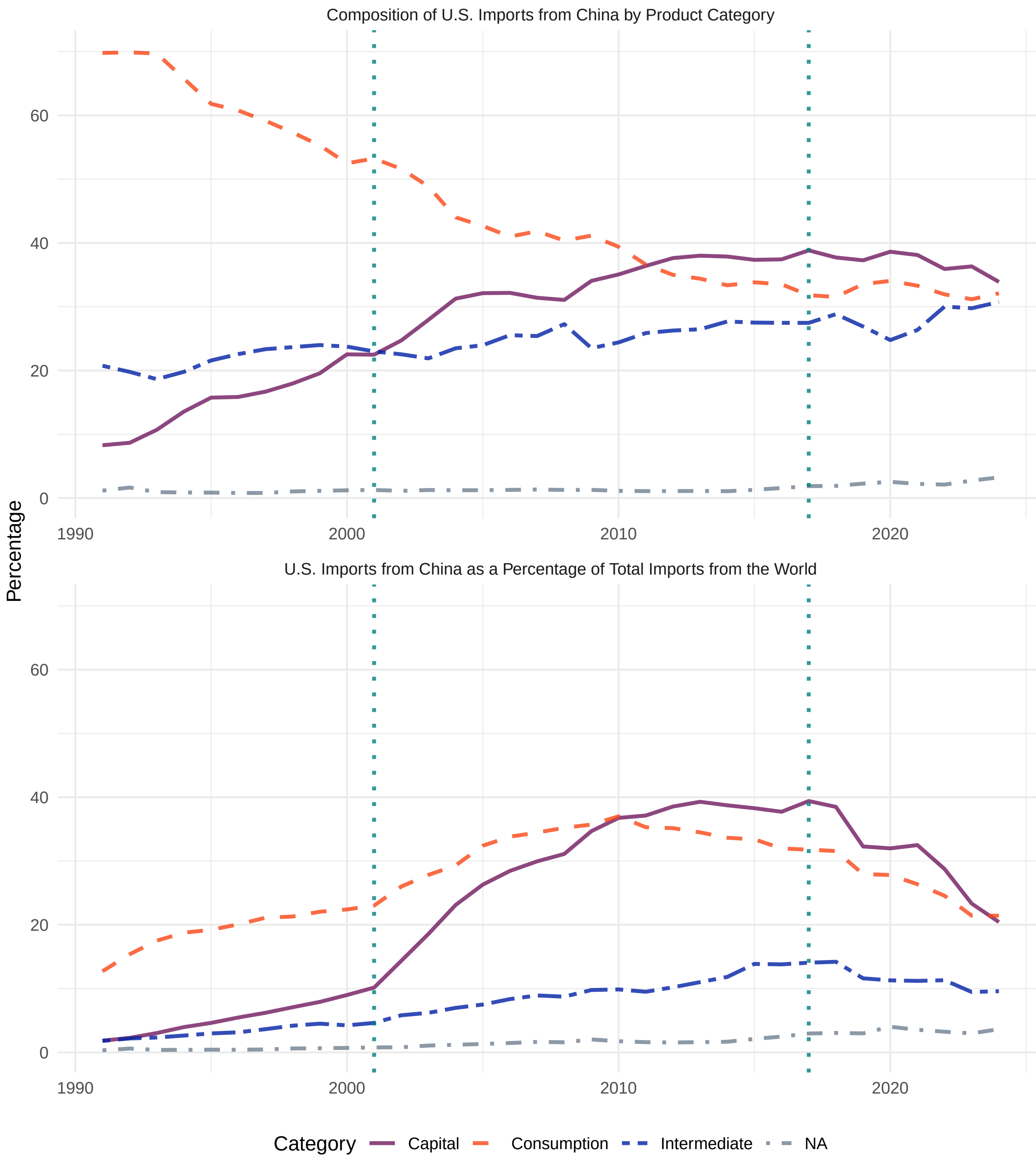
The figure visualizes the breakdown of the level of export and import tariffs, by the industries (vertical) and the stages of trade war (horizontal). The darker the color, the higher the tariff imposed. Figure (a) presents the level of tariff on the goods imported from China by the United States. Figure (b) shows the level of tariff on the goods exported to China by the United States. The industries are ranked by the change of exposures before and post the trade war.

Figure A.2. Share of Inputs Sourced and Outputs Consumed by the Same Industry



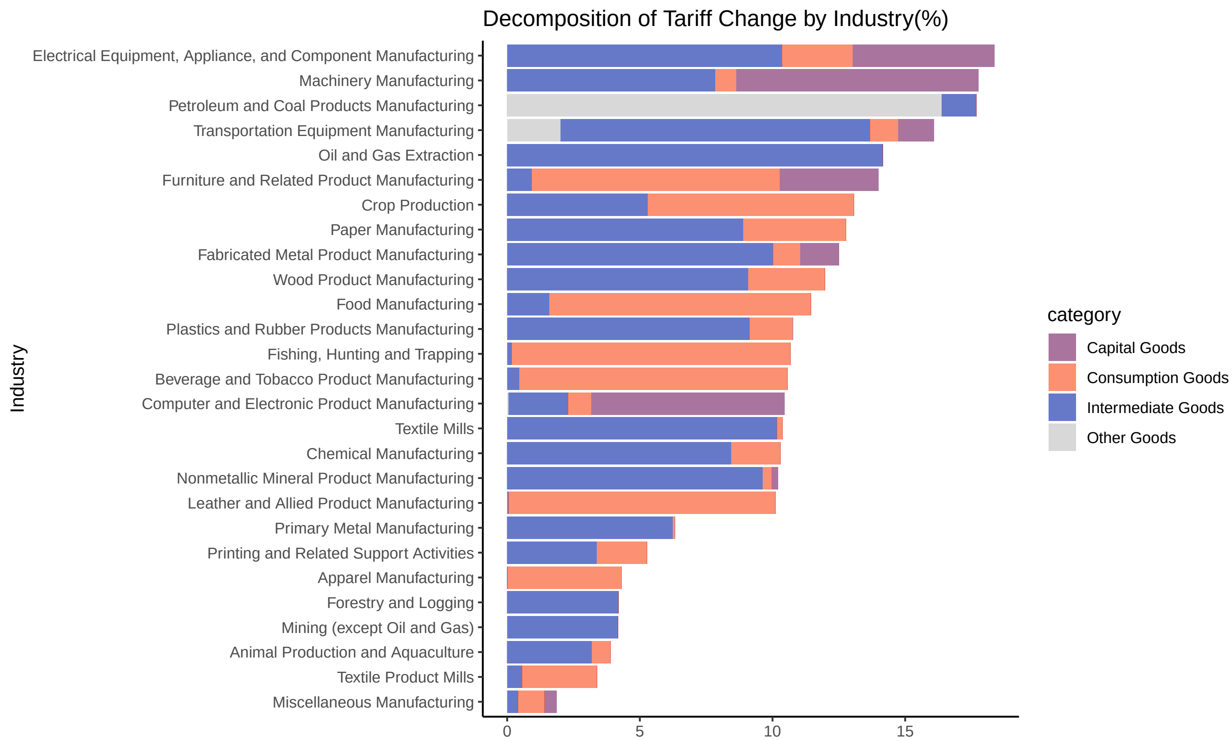
This figure illustrates the input-output linkages within industries, showing the percentage of inputs sourced from the same industry (orange line) and the percentage of outputs consumed by the same industry (blue line) across different industries. The x-axis shows the percentage share. The figure highlights the extent to which industries rely on their own outputs as inputs and consume their own products internally. The industries are ranked based on the percentage of inputs sourced from the same industry (Upstream Weight).

Figure A.3. 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 down 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.4. 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
Total 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 quarterly spending, relative to the same household's mean level of spending during the pre-shock quarters.	NielsenIQ
Spending	A household-product-quarter level variable that equals the total spending by a household on a product in a given quarter.	NielsenIQ
Price	A household-product-quarter level variable that equals the average price paid by a household on a product in a given quarter.	NielsenIQ
Quantity	A variable at the household-product-quarter level representing the total quantity (in units) of a specific product purchased by a household in a given quarter.	NielsenIQ
Treat	A household-quarter level dummy variable that turns on when the household resides in a county most exposed to the import tariffs imposed during the trade war.	NielsenIQ
Treat (Upstream)	A dummy variable that turns on when two conditions are met: (1) Treat is set to one, and (2) the household being treated is located in a county where its industries' upstream import exposure exceeds the median level of all counties being treated.	Bureau of Economic Analysis
Treat (Downstream)	A dummy variable that turns on when two conditions are met: (1) Treat is set to one, and (2) the household being treated is located in a county where its industries' downstream import exposure falls below the median level of all counties being treated.	Bureau of Economic Analysis
<50k	A dummy variable that equals one if the household has an annual income less than 50k.	NielsenIQ
50k-100k	A dummy variable that equals one if the household has an annual income between 50k and 100k.	NielsenIQ
>100k	A dummy variable that equals one if the household has an annual income greater than 100k.	NielsenIQ
Generation B	A dummy variable that equals one if the household heads were born before 1964.	NielsenIQ
Generation X	A dummy variable that equals one if the household heads were born between 1964 and 1980.	NielsenIQ
Generation M	A dummy variable that equals one if the household heads were born between 1980 and 1996.	NielsenIQ

Variable name	Description	Source
Employment	A county's quarterly total employment across industries.	Bureau of Labor Statistics
Wage	A county's employment-weighted average of weekly wage in a quarter. Expressed in dollars.	Bureau of Labor Statistics
Wage Growth	The Year-on-Year growth of a county's wage in a quarter. Expressed in percentage.	Bureau of Labor Statistics
Wage % Chg	The relative change of a county's wage to the average of the county's pre-trade war wage. Expressed in percentage.	Bureau of Labor Statistics