From Border to Basket:

Pass-Through of U.S. Trade Policy to Consumers*

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PRELIMINARY AND INCOMPLETE:

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Abstract

To what extent do import tariffs raise retail prices? We seek to answer this question within the context of the U.S.-China trade war of 2018-2019 by combining product-level country-of-origin data with scanner data on both prices and quantities for a broad sample of individual products. We document the first evidence of positive pass-through into U.S. store prices, with an average pass-through rate of 15%. By tracking specific barcodes over time, we document the within-category distribution of tariff elasticities across products: tariff pass-through is increasing in product-specific market share, whereas quantity effects are decreasing in market share. Estimates of average category-level tariff elasticities therefore miss a crucial feature of the product market response: products exhibiting high price pass-through are precisely the varieties with little to no quantity response.

JEL Categories: E31, F13, F14, F31, L11.

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1 Introduction

The U.S.-China trade war of 2018-19 marks a dramatic and economically significant departure from over 40 years of increased globalization via trade agreements, reduced tariffs, and greater policy certainty. This remarkable episode has generated a growing literature documenting its many economic consequences, for the U.S. (Amiti et al. 2019; Fajgelbaum et al. 2020; Cavallo et al. 2021; Autor et al. 2024), China (Chor and Li 2024), as well as third-party countries (Fajgelbaum et al. 2024). Yet several open questions remain, including the extent to which U.S. import tariffs affected retail prices, quantities, and availability of final consumer products at U.S. stores.

Understanding the extent to which tariffs pass through to consumers is crucial for understanding the incidence of tariffs and their costs for households within the country imposing such policies. While several papers have convincingly documented close to complete tariff pass-through into U.S. prices at the border via customs data – such as Amiti et al. (2019), Fajgelbaum et al. (2020), and Cavallo et al. (2021) – there remains remarkably little evidence for any effect of these tariff changes on prices faced by U.S. households at U.S. stores: Cavallo et al. (2021) estimate pass-through into U.S. retailer prices of only 3.5%, and this estimate is statistically indistinguishable from zero at standard confidence levels. This "missing" pass-through is particularly relevant given the very real data limitations associated with estimating tariff pass-through either via customs data or price data scraped from individual retailer websites.[1]

This paper links U.S. store-level scanner data to barcode-specific origin country information in order to estimate the pass-through of import tariffs on Chinese goods into prices faced by U.S. households. More specifically, we make use of NielsenIQ's Retail Scanner Data, which covers around 50,000 participating grocery, drug, mass merchandiser, and other stores. An important feature of our dataset is the combination of both price and quantity data for a constant set of barcodes over time, thus alleviating any concerns of bias via aggregation and compositional changes. We set our level of observation as a barcode-retail chain pair and es-

[1] Customs data are generally not able to follow the price and quantity changes of a specific product over time. Rather, they capture aggregate expenditure-weighted average changes in prices and quantities sold at the sector or product category level.

timate the price and quantity effects of tariffs using a triple-difference strategy. By including barcode-retailer, retailer-time, category-time and country-time fixed effects, we compare outcomes of targeted Chinese barcodes to non-Chinese barcodes within the same category and we compare this differential outcome to the same comparison in non-targeted product categories. Thus, we are able to control for any movements in exchange rates, category-specific demand/supply changes, and shocks to specific retailers via a triple-difference identification strategy.

We provide the first direct evidence of positive pass-through of tariffs into U.S. final consumer prices. Specifically, we estimate an average pass-through of approximately 15%. Reassuringly, our estimates of the quantity response associated with these tariffs is close to estimates found elsewhere using customs data: we find significant substitution away from Chinese varieties with an estimated average tariff elasticity of -0.54. These results are robust to excluding 2020 data from our analysis, thus controling for any measurement error introduced by the Covid-19 pandemic.

By leveraging data which tracks specific barcodes over time, we are able to check for pre-trends in both our price and quantity elasticity estimates by implementing an event study design. We find no evidence of pre-trends and thus interpret our estimates as plausibly causal effects of tariffs on store-level prices and quantities sold.[2] In addition, we decompose the quantity response into two dimensions: the number of stores exhibiting non-zero sales of a given barcode and the sales per store of a given barcode within a specific retail chain. We find that the extensive margin – stores dropping barcodes – accounts for two thirds of the observed quantity elasticity, while *within*-store substitution accounts for only a third.

We then use our barcode-level data to estimate the distribution of tariff elasticities across the distribution of product-specific market shares. We find a significant and positive relationship between tariff pass-through and market share, such that barcodes in the lowest market share quintile exhibit a pass-through rate of only 7% while barcodes in the highest market share bin exhibit pass-through of 27%. Average pass-through is 26% for a third of all

[2]We do find evidence of asymmetric seasonality in prices for product categories targeted with tariffs. This seasonality is prevalent prior to any change in trade policy, and is most noticeable for products ultimately targeted by tariffs. We therefore include seasonality controls interacted with whether a product is ultimately targeted by a tariff.

Chinese grocery export expenditure in the U.S. market – the third of expenditure associated with the highest market share barcodes – whereas the two thirds of expenditure accruing to low-market share barcodes exhibits an average pass-through of only 9%.

Interestingly, we document the opposite pattern for substitution effects: the quantity tariff elasticity is -0.843 for barcodes in the lowest market share bin while barcodes in the highest market share bin exhibit a quantity elasticity estimate of precisely zero. Our paper therefore highlights a key omission from studies which estimate average tariff effects at the category, or sector, level: those varieties which exhibit positive, and substantial, tariff pass-through are exactly the varieties which do not contribute to the aggregate tariff substitution elasticity.

It is important to note that this result is somewhat at odds with the canonical heterogeneous firms framework of Atkeson and Burstein (2008), in which cost pass-through is generally decreasing in market share across heterogeneous varieties of the same sector.[3] Instead, models featuring two-sided bargaining power – as in Alviarez et al. (2023) – may provide some intuition for the results described here. In particular, if buyer (retailer) bargaining power is stronger for low market share producers (varieties), these low mark-up producers may not be able to pass-through a cost shock to retailers who possess the outside option of simply dropping targeted products from their shelves. On the other hand, high market share producers may have more bargaining power vis-a-vis the retailer, and are therefore better able to pass-through at least some portion of a cost shock. That is, monopsony power may dampen observed pass-through at the low-end of the market share distribution.

While this project is still a work in progress, future iterations/drafts will include the following additional results:

1. **Anti-competitive effects:** We can leverage our data to check whether tariffs applied to Chinese exports within a given product category led to increased prices offered by non-Chinese barcodes within the targeted category. Analysis is ongoing, but initial estimates suggest a lack of anti-competitive effects, such that non-targeted products

[3]Of course as a firm becomes a complete monopolist, pass-through again increases, such that the relationship is U-shaped. At the product level, however, the empirically relevant range of market shares is generally below 5%, suggesting a lack of perfect monopoly power.

within the same product category are a viable control group for estimating tariff pass-through.

2. **Entry and exit:** Since we track barcodes over time, we are able to estimate the entry and exit effect of tariffs on specific barcodes, and thus document the compositional changes in the product market associated with tariffs. While analysis is ongoing, our preliminary results suggest that composition effects may lead to over-estimates of tariff pass-through, with pass-through estimates potentially as high as 70%. This differential in pass-through estimates (15% versus 70%) may be attributable to unbalanced entry and exit and therefore "Metzler effects" (Metzler 1949), in which average ex-tariff prices respond to tariffs via the composition of varieties exported. See Ludema and Yu (2016) for empirical evidence of similar effects in the context of exchange rate shocks.

3. **Heterogeneous effects by retailer characteristics:** While the current draft emphasizes heterogeneous effects by barcode characteristics (see Section 5), we will also include a study of how tariff effects vary by retailer market share. By combining buyer and seller market share within the same estimating equation, we can credibly separate pass-through into components associated with monopoly power and monopsony power. We therefore aim to contribute to the growing literature documenting these effects on measured tariff pass-through (Alviarez et al. 2023).

4. **Within- versus across-firm substitution:** Given that barcodes are associated with a given brand, our data provides a unique opportunity to study whether tariff substitution occurrs primarily within brands or whether tariffs induced substitution across brands, depending on their initial exposure via production locations.

Related literature: This paper fits into a growing empirical literature on the economic consequences of the U.S.-China trade war. Using customs data at the HS 10-digit level, both Amiti et al. (2019) and Fajgelbaum et al. (2020) find that tariffs led to a reduction in import/export quantities, but no change in the ex-tariff prices received by exporters. In other words, there was near complete pass-through of tariffs into prices at the border, and as a result the cost of tariffs was born by U.S. consumers and importers. Our work contributes

to this literature by providing some of the first estimates of how U.S. import tariffs affected final consumer prices, quantities and product availability, using barcode-level data.

The closest paper to ours is Cavallo et al. (2021), who also study tariff pass-through into U.S. store prices. Compared to their work, our analysis crucially benefits from data on both prices and quantities at the barcode level, covering the sales of around 70 retail chains. This allows us to study the extent to which U.S. households substituted away from Chinese products that were affected by the tariffs, and to investigate heterogeneity in pass-through by specific product characteristics such as market share. We therefore contribute to the growing literature documenting the economic consequences of the U.S.-China trade war.[4]

By estimating heterogeneous pass-through across varieties within product categories, this paper provides novel evidence regarding the distributional effects of cost shocks on heterogeneous exporters (Goldberg and Hellerstein 2008; Berman et al. 2012; Amiti et al. 2014; Auer and Schoenle 2016). While our results are potentially at odds with the predictions of Atkeson and Burstein (2008), models of pass-through with two-sided bargaining power may be able to rationalize the findings documented here (Alviarez et al. 2023).[5]

2 Data

We bring together a number of data sources for the empirical analysis of this paper: i) barcode-level price and expenditure from NielsenIQ Retail Scanner Data, ii) barcode-level country-of-origin data purchased from Label Insight, iii) barcode-level country-of-origin data scraped from the website of a large U.S. retailer, iv) tariff data at the eight-digit Harmonized System (HS) level from the U.S. International Trade Commission (USITC), v) firm identifiers from GS1, and vi) a concordance between Nielsen product modules and HS-10 digit codes (constructed by the authors).[6]

[4] As described in Fajgelbaum and Khandelwal (2022). Examples include: Charbonneau and Landry (2018); Fetzer and Schwarz (2021); Benguria et al. (2022); Blanchard et al. (2024); Handley et al. (2025). See Bown (2021) for a full timeline of the events which constitute the U.S.-China trade war.

[5] By focusing our analysis on U.S. stores, we also contribute to the literature documenting the relationships between foreign producers, domestic retailers, and trade shocks (Raff and Schmitt 2006, 2009; Eckel 2009; Basker and Van 2010; Basker et al. 2012; Raff and Schmitt 2012, 2016; Meinen and Raff 2018; Cole and Eckel 2018; Jaccard 2023).

[6] This is an extension of the concordance between Nielsen product modules and HS-6 digit codes used in Bai and Stumpner (2019).

2.1 Price and Expenditure

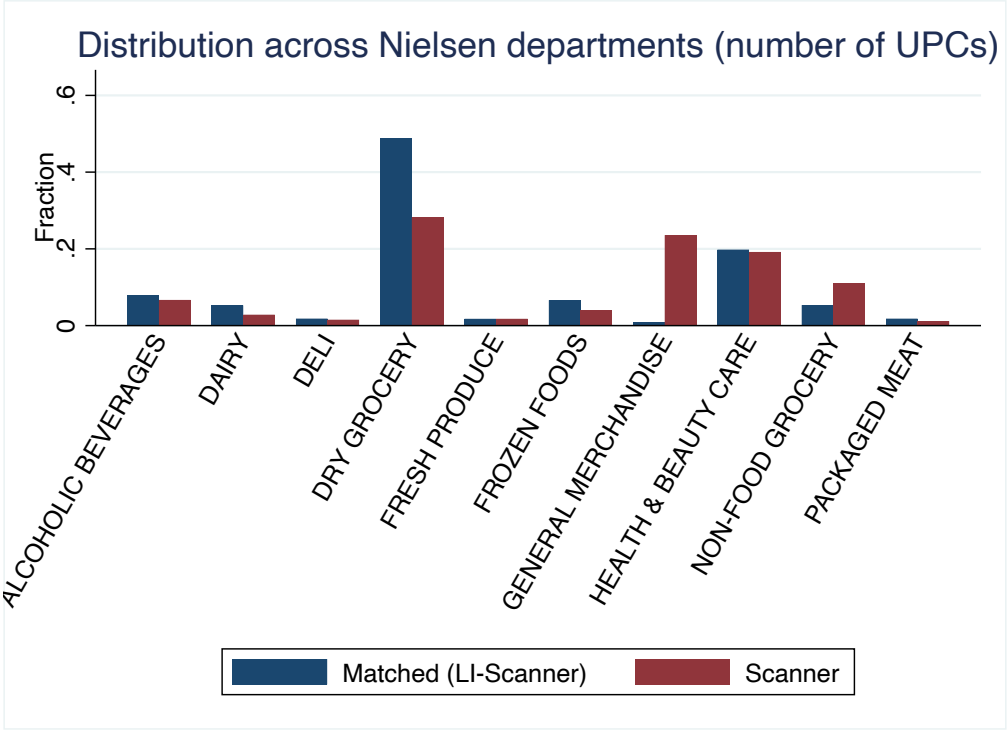
For information on prices and expenditures at the barcode-level, we make use of the NielsenIQ Retail Scanner Data, over the period 2015-20. Products from all Nielsen-tracked categories are included in the data, such as alcoholic beverages, dairy, deli, dry grocery, fresh produce, frozen foods, packaged meat, general merchandise, health and beauty care, and non-food grocery. Depending on the year, data are included from approximately 30,000-50,000 participating grocery, drug, mass merchandiser, and other stores.

The raw data is available at the barcode-store-week level. For the analysis, we build a panel dataset of prices and expenditures at the barcode-retailer-month level. To abstract away from changes in the set of reporting stores over time, we focus on the set of stores that report positive sales in every year of our sample period ($n = 29,054$). To aggregate sales and prices at the retailer level, we make use of the NielsenIQ retail chain identifiers. Thus, one can consider an observation in our sample as consisting of, for example, quantities sold and average prices received across the entire U.S. market for a specific size of Coca-Cola sold at all Walmart stores in a given month.

2.2 Country of Origin

One limitation of the Retail Scanner Data when used in empirical studies of international trade is the lack of information regarding a product's country of origin. To overcome this, we supplement it with two separate data sources that provide this information at the barcode level. First, we use a proprietary dataset purchased from Label Insight, a private firm specializing in the provision of detailed product attribute data. Second, we scrape data from the website of a large U.S. retailer, which further improves our product coverage. Together, these two sources provide us with country-of-origin data for 275,364 barcodes, corresponding to 22% of the total number of Nielsen barcodes during our sample period. Because Label Insight prioritizes products with the highest volume of sales, these matched barcodes account for 61% of total expenditure in the Retail Scanner data. As shown in Figure 1, the distribution across Nielsen departments (both in terms of number of UPC codes and expenditure) looks similar for the matched and broader samples.

Figure 1: Distribution of Barcodes by Department



Notes: Figure 1 provides the distribution of barcodes across NielsenIQ product departments according to the raw scanner data (red) and the merged Label Insight-NielsenIQ dataset used in this paper (blue).

We are among the first studies in economics to use barcode-level country-of-origin data, and to the best of our knowledge, the only study to use this information to study tariff pass-through into final consumer prices.[7]

2.3 Tariff Data

Figure 2 shows the weighted average tariff that the U.S. Government has applied on imports from China over time, using 2017 import weights. The tariff increase was substantially lower in HS codes that map into NielsenIQ consumer product modules than in other categories of goods, but was still substantial.[8] The aggregate tariff increase applied to Chinese goods present in the NielsenIQ data from early 2017 to the peak at the end of 2019 was over 7ppt, compared to a pre-2018 baseline average tariff rate of around 3%.

[7]See Jaccard (2023) and McCully et al. (2024) for other papers using the Label Insight data.

[8]The initial two waves of the U.S.-China trade war focused heavily on intermediates (chemicals and machinery), rather than consumer goods.

Figure 2: Trade War Tariffs by Dataset

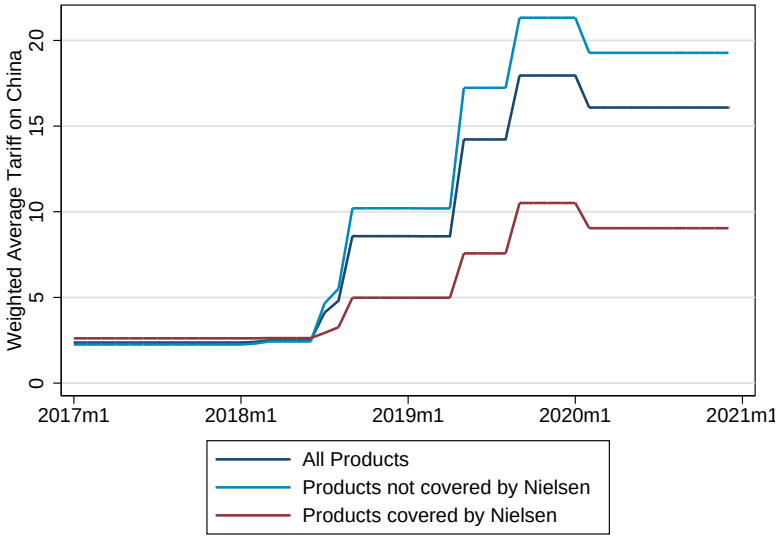
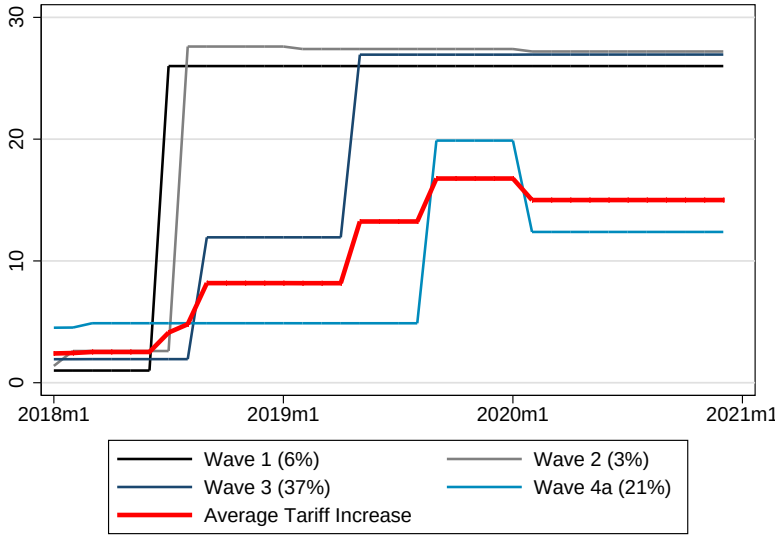


Figure 3: Trade War Tariffs by Wave within NielsenIQ Sample



Notes: Figure 2 provides the average tariff rate applied by the U.S. to imports from China over time, decomposed into categories covered by the NielsenIQ data and all other categories. Figure 3 provides the average tariff increase over time within NielsenIQ categories, and denotes the total share of categories within the NielsenIQ data subject to the different tariff waves applied to imports from China.

There were four waves of tariff changes associated with the 2018-2019 trade war. Figure 3 plots the tariff rate applied to Chinese goods by tariff wave, as well as the average tariff increase applied to Chinese goods within all NielsenIQ product categories. There are over 400 consumer good categories within the scanner data and roughly 70 of them are completely

unaffected by the U.S.-China trade war. However, these categories account for over 50% of all U.S. imports from China that we observe in the NielsenIQ scanner data. Waves 1 and 2 account for only a very small share of categories and imports in the NielsenIQ data, as these tariffs targeted intermediate goods. The focus of this paper will therefore be on the tariff changes associated with waves 3 and 4a.

As shown in Figure 3, the wave 3 tariffs experienced two increases: an increase from 2.5% to 12.5% in September 2018, and a further increase to 27.5% in May 2019. Wave 4a categories experience a tariff increase from 5% to 20% in August 2019, with a reduction to 12.5% in early 2020. Given complications arising due to the Covid-19 pandemic, we will provide results using all categories and separately for each tariff wave. We will also explore estimates both including and excluding data from 2020.

3 Empirical Model

The goal of this paper is to estimate both the pass-through of tariff changes into U.S. store prices as well as substitution which occurrs in response to these tariffs. We leverage unique features of our data – product-specific prices and quantities over time – to implement a triple-difference identification strategy at the barcode level. That is, we compare barcodes produced in China to non-Chinese goods within the same product category and compare this difference between targeted and non-targeted categories before and after tariffs were implemented. A key feature of the dataset used here is consistent and well-defined products – barcodes – such that the tariff elasticities we estimate are within-product for both prices and quantities.[9]

Consider some outcome associated with barcode i at retail chain r in month t, y_{irt}. Barcode i belongs to product category $c(i)$ and is produced in origin country $j(i)$. Our main explanatory variable of interest is therefore the tariff rate applied by the U.S. to category c and country j in month t: τ_{jct}.

Equation 1 provides our triple-difference estimating equation, with β capturing the effect

[9]Both Flaaen et al. (2020) and Cavallo et al. (2021) use U.S. retailer-level data but both are limited to studying prices, as they do not have quantity data.

of changes in tariffs on outcome y_{irt} at the barcode-retailer level.

$$\ln(y_{irt}) = \beta \ln(1 + \tau_{jct}) + \alpha_{irt} + \gamma_{i,q(t)} + \epsilon_{irt} \tag{1}$$

The vector α_{irt} denotes a set of fixed effects, such that:

$$\alpha_{irt} = \alpha_{ir} + \alpha_{rt} + \alpha_{c(i),t} + \alpha_{j(i),t}$$

This specification accounts for level differences across both retailers and barcodes by including barcode-retailer fixed effects (α_{ir}). We also control for any period-specific shocks to retail chain r (α_{rt}) or category-specific shocks which affect all barcodes within a given category, regardless of origin country or retail chain at which that barcode is sold (α_{ct}). Finally, we control for country-period fixed effects, such that any exchange rate shocks or demand shocks which are origin-specific are controlled for (α_{jt}).

The vector $\gamma_{i,q(t)}$ denotes seasonality controls which are specific to tariff-targeted goods. In analyzing our raw price and sales data, we find strong evidence of seasonality that is specific to the categories targeted by tariffs. Such seasonality is not captured by the fixed effects described above as these shocks are not specific to Chinese exports or specific categories, but the specific interaction of Chinese varieties within tariff-targeted categories. We therefore include a vector of seasonality controls, in which $\Gamma_i = 1$ is a treatment indicator equal to one if a given barcode is ultimately targeted with a tariff and zero otherwise.[10] We interact this indicator with indicator variables at the quarter level, such that $q(t) = 1$ denotes that period t is in the first quarter.

$$\gamma_{i,q(t)} = \sum_{q'=1}^{4} \gamma_{q'} \times \Gamma_i \times \mathbf{1}[q(t) = q']$$

As mentioned earlier, this specification can be interpreted as a triple-difference estimator. If y_{irt} is the price of a given barcode, then Equation 1 is a comparison between Chinese and non-Chinese barcodes across tariff-targeted and non-targeted categories before and after

[10] That is, if the combination of product category $c(i)$ and origin country $j(i)$ are ultimately targeted with a tariff by the U.S., then $\Gamma_i = 1$.

tariff implementation. We focus on three outcomes of interest at the barcode-retailer pair level: prices, total quantity of units sold, and the number of stores within a retail chain exhibiting non-zero sales of that barcode in a given month.

Event study design: In addition to the triple-difference estimator described above, we employ an event study design to check for pre-trends. That is, we estimate Equation 2 and plot the estimate vector β_γ.

$$\ln(y_{irt}) = \sum_{\gamma=\underline{T}}^{\bar{T}} \beta_\gamma \times \Gamma_i \times \mathbf{1}[t = T - \gamma] + \alpha_{irt} + \gamma_{i,q(t)} + \epsilon_{irt} \tag{2}$$

where T denotes the date of the first tariff change.

Heterogeneous effects of tariffs: We also explore heterogeneous effects of tariffs across barcode characteristics, and report these results in Section 5. In particular, we study how pass-through and substitution differs by initial market share of each barcode. We therefore place barcodes into bins based on their aggregate market share in 2017, before any tariff changes were implemented, and use Equation 3 to estimate differential tariff effects across barcodes according to their market share bin.

$$\ln(y_{irt}) = \beta^s \ln(1 + \tau_{jct}) + \alpha_{irt} + \gamma_{i,q(t)} + \epsilon_{irt} \tag{3}$$

In Equation 3, β^s captures these heterogeneous effects by market share bin s.

4 Results

This section provides baseline results associated with our triple-difference estimator outlined in Equation 1, as well as a discussion of pre-trends and the event study estimates described in Equation 2. We then decompose the quantity effects into an intensive and extensive margin response, where the extensive margin denotes the number of stores within a given chain stocking a specific barcode. Finally, we discuss heterogeneity in tariff effects across market share bins.

4.1 Headline Estimates: Tariff Pass-through and Substitution

Table 1 provides our main estimates of tariff pass-through and substitution associated with the tariffs placed on Chinese imports over the period 2018–2019.

Columns (1)-(3) provide estimates associated with prices as the dependent variable, such that these estimates can be interpreted directly as pass-through estimates.[11] Column (1) provides our baseline estimate, as outlined in Equation 1, with all data years from 2014-2020 included. Column (2) separates these estimates into those product categories associated with tariff wave 3 and those associated with tariff wave 4a. Finally, column (3) drops 2020 in order to reduce the noise associated with the Covid-19 pandemic, which therefore limits the sample to only categories affected by tariff wave 3.[12] Columns (4)-(6) provide the same estimates but with units sold as the dependent variable.

We estimate average tariff pass-through of 13.3%, when averaged across both tariff waves and including the year 2020. This estimate is significantly distinguishable from zero at levels of 99%. Interestingly, the pass-through elasticity seems invariant to the tariff wave being studied. This result is interesting as the magnitude of tariff changes differed substantially between wave 3 and wave 4a, yet the pass-through elasticity associated with the two waves are not statistically distinguishable at standard significant levels. When 2020 is omitted, the estimated pass-through coefficient increases slightly to 15.4%.

These results represent the first estimates to date of positive, and statistically significant, pass-through of the tariffs levied by the Trump Administration on Chinese exports. While Cavallo et al. (2021) find pass-through into border prices of almost 100% – which is in line with Amiti et al. (2019) and Fajgelbaum et al. (2020) – they are unable to find any effect of the China-specific tariffs on prices offered by U.S. stores.

In line with other papers, we find a significant and negative quantity effect of tariffs on units sold. Column (4) of Table 1 provides our headline substitution elasticity: every 10% increas in tariffs levied on Chinese goods decreased the units sold of these products by 5.43% such that the quantity tariff elasticity is -0.543. We find no significant effect of

[11] That is, an estimate of $\beta = 0.133$ implies a pass-through of tariffs into store-level prices of 13.3%.

[12] Tariff wave 4a was implemented in the Fall of 2019, thus limiting the pre-Covid sample available for estimation.

Table 1: Estimates of Tariff Pass-through and Substitution

	(1) log Price	(2) log Price	(3) log Price	(4) log Quantity	(5) log Quantity	(6) log Quantity
$\log(1+\tau)$	0.133***			-0.543***		
	(0.041)			(0.172)		
$\log(1+\tau) \times$ W3		0.133***	0.154***		-0.538***	-0.516***
		(0.041)	(0.039)		(0.169)	(0.164)
$\log(1+\tau) \times$ W4		0.161**			-0.111	
		(0.070)			(0.300)	
Wave 3			✓			✓
Sample			<=2019			<=2019
R^2	1.00	1.00	1.00	0.97	0.97	0.98
Observations	35043587	35043587	16676864	35043587	35043587	16676864
α_{ir}	✓	✓	✓	✓	✓	✓
α_{rt}	✓	✓	✓	✓	✓	✓
α_{ct}	✓	✓	✓	✓	✓	✓
α_{jt}	✓	✓	✓	✓	✓	✓

*Notes: This table provides estimates of β from applying OLS to Equation 1. Columns (1)-(3) define y_{irt} as the average price at barcode-retailer-month irt. Columns (4)-(6) define y_{irt} as the quantity of units sold. The interactions depict an interaction between tariff changes and an indicator for that tariff change being associated with wave 3 (W3) or wave 4a (W4). Standard errors are clustered at the barcode-retailer-pair level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.*

tariffs on units sold for the wave 4a product categories, and the coefficient – while negative – is reduced in magnitude to almost one fifth of the headline estimate. This likely reflects the lack of post-tariff change periods to study and measurement error associated with the Covid-19 pandemic.

Taken together, our price and substitution estimates suggest a tariff quantity elasticity of -0.543, a pass-through elasticity of 0.133, and a price elasticity of approximately four.[13]

4.2 Pre-trend Analysis and Event Study Estimates

In order to validate the estimates presented in Table 1, we estimate the event study specification outlined in Equation 2. Since the two tariff waves – wave 3 and wave 4a – were implemented at different times, we estimate four separate event study models. That is, price and quantity estimates separately for the two tariff waves. These event study figures are provided in Appendix A.2 as Figures A.1, A.2, A.3, and A.4.

[13]By "price elasticity", we refer to the implied demand elasticity associated with the quantity and price tariff elasticity, such that $(-0.543/0.133) \approx 4$.

Reassuringly, we find no evidence of pre-trends associated with either the price or quantity estimates presented earlier. While outside the scope of this paper, these estimates also highlight the sensitivity of pass-through behavior to both the time since tariff implementation and the size of the tariff change. While prices responsed only modestly to the 10% tariff increase for wave 3 products, the additional increase of 15 percentage points in the tariff rate is accompanied with a clear and sustained increase in prices. Similarly, the wave 4a categories which experienced a decrease in tariffs shortly after the initial increase exhibit prices which return to trend after the reversal in policy.

4.3 The Margins of Tariff Substitution

This section decomposes the estimated quantity response into two margins: the number of stores within a retail china which exhibit non-zero sales of a given barcode, and the total units sold of a given barcode at a retail chain across all stores. Specifically, Table 2 provides estimates of β from Equation 1 with columns (1)-(3) representing, respectively, the effect of tariffs on total quantities sold, the effect of tariffs on the number of stores, and the effect of tariffs on units sold per store.

The aggregate quantity effect remains as estimated in Table 1, with a tariff elasticity of -0.543***. As shown in column (2) of Table 2, the extensive margin, or the number of stores stocking a given barcode, accounts for almost two thirds of the aggregate effect. That is, the elasticity of store counts to tariffs for a given barcode-retailer pair is -0.347***. The elasticity of units sold per store, provided in column (3), is -0.196*, therefore accounting for a third of the total effect.

This decomposition is useful in making sense of the potentially large tariff quantity elasticity estimated in Table 1. Recall that our headline estimate of price pass-through is 0.133*** while our headline quantity elasticity is -0.543***, implying a demand elasticity of approximately four. At the intensive margin, however, our quantity elasticity is -0.196, implying a within-store demand elasticity of 1.5.

This section therefore provides evidence that pass-through into store prices was non-negligible and averaged approximately 15% (when 2020 is excluded). The substitution response was significant and negative, with a tariff elasticity of approximately 0.5 and an im-

Table 2: Quantity Response: Intensive and Extensive Margin

	(1) log Quantity	(2) log Stores	(3) log Qty per Store
$\log(1+\tau)$	-0.543***	-0.347***	-0.196*
	(0.172)	(0.124)	(0.111)
R^2	0.97	0.95	0.98
Observations	35043587	35043587	35043587
α_{ir}	✓	✓	✓
α_{rt}	✓	✓	✓
α_{ct}	✓	✓	✓
α_{jt}	✓	✓	✓

*Notes: This table provides estimates of β from applying OLS to Equation 1. Columns (1)-(3) define y_{irt} as, respectively, units sold at barcode-retailer-month level, the number of stores exhibiting non-zero sales of barcode i within retail chain r and month t, and the quantity of units sold per store within barcode i, retailer r, and month t. Standard errors are clustered at the barcode-retailer-pair level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.*

plied demand elasticity of four. However, two thirds of this quantity response is attributable to store behavior, rather than substitution by consumers within store. We now turn to an analysis of the heterogeneous effects of pass-through and substitution across barcodes.

5 Heterogeneity in Pass-through and Substitution

5.1 Market Share Bins: Qualitative Facts

This section provides a brief overview of how we constructed the market share bins and some qualitative description of the distribution of barcodes across these bins. In constructing market share at the barcode level, we first aggregate all revenue accruing to barcodes within a given category c for the calendar year 2017, across all retail chains. Denote this aggregate expenditure as X_c^{2017}. We then calculate the same 2017 expenditure but at the barcode level: X_i^{2017}. Finally, we calculate within-category market share: $s_i = X_i^{2017}/X_{c(i)}^{2017}$.

Table A.1 in Appendix A.1 provides the distribution of both barcodes and expenditure across the five market share bins constructed for our analysis, both for all barcodes and those barcodes specifically from China. While the bins are constructed to (roughly) balance expenditure across these bins, this naturally leads to a skewed distribution of barcodes. 86% of all barcodes are in the lowest market share bin, implying their within-category 2017 market

share is less than 0.25%. Yet only 26% of all expenditure accrues to these same barcodes. At the other end of the distribution, only 2.2% of all barcodes are in the highest market share bin, which is reserved for barcodes with a within-category market share greater than 2.50%. Yet 20% of all expenditure accrues to these 2% of barcodes.

While Chinese barcodes are more concentrated in the lower market share bins, the distributions overlap considerably. 87% of all expenditure on Chinese barcodes is concentrated in the lowest market share bin, which hosts 30% of all Chinese barcodes. At the high end of the distribution, 1.6% of all Chinese barcodes are in the highest market share bin, but these barcodes account for 14% of all expenditure on Chinese barcodes.

5.2 Tariff Effect Heterogeneity by Market Share

Table 3 provides estimates of price pass-through, substitution, and the number of stores per barcode-retailer pair decomposed into separate effects at the market share bin level. Recall that s_1 denotes the smallest market share bin, and s_5 the largest. As always, these estimates are recovered in the presence of all fixed effects outlined in Equation 3.

Column (1) provides estimates of heterogeneous tariff pass-through intro prices across Chinese barcodes. We estimate pass-through elasticities which are increasing in market share, with an almost monotonic relatinoship (the second and third bins exhibit pass-through that is indistinguishable from each other). The range of possible pass-through values is also striking: barcodes in the lowest market share bin exhibit pass-through of only 7.1%, whereas barcodes in the highest market share bin exhibit pass-through of 27.6%. Thus, even within product categories, we find that high market share varieties exhibit tariff pass-through rates that are almost four times larger than low market-share varieties.

For the quantity tariff elasticity estimates – provided in column (2) – the opposite pattern occurs. Barcodes in the lowest market share bin exhibit the largest elasticity by magnitude: -0.843***. While none of the other estimates are significant, they are also much smaller in magnitude. From smallest to larger market share bin, we estimate quantity tariff elasticities of -0.843***, -0.214, -0.265, -0.472, and 0.029. While bins 2, 3, and 4 exhibit negative, if not statistically significant, estimates of quantity effects, varieties in the largest market share bin exhibit estimates that insignificant statistically and in terms of their magnitude. Indeed,

Table 3: Pass-through and Substitution by Market Share Bins

	(1) log Price	(2) log Quantity	(3) log Stores
$\log(1+\tau) \times s_1$	0.071**	-0.843***	-0.621***
	(0.035)	(0.240)	(0.178)
$\log(1+\tau) \times s_2$	0.111	-0.214	0.065
	(0.109)	(0.315)	(0.394)
$\log(1+\tau) \times s_3$	0.107*	-0.265	-0.133
	(0.060)	(0.308)	(0.376)
$\log(1+\tau) \times s_4$	0.247***	-0.472	-0.304
	(0.082)	(0.335)	(0.244)
$\log(1+\tau) \times s_5$	0.276***	0.029	0.132
	(0.073)	(0.383)	(0.247)
R^2	0.997	0.968	0.948
Observations	35043587	35043587	35043587
α_{ir}	✓	✓	✓
α_{rt}	✓	✓	✓
α_{ct}	✓	✓	✓
α_{jt}	✓	✓	✓

*Notes: This table provides estimates of β^s from applying OLS to Equation 3. Columns (1)-(3) define y_{irt} as, respectively, the the average price at barcode-retailer-month irt, the number of units sold, and the number of stores exhibiting non-zero sales. Tariff changes are interacted with five market share bins, such that 2017 barcode-specific market share is increasing in s. See Table A.1 for summary statistics regarding bins. Standard errors are clustered at the barcode-retailer-pair level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.*

the quantity elasticity for bin five is a fairly precise zero estimate.

Finally, as depicted in column (3), we find that store exit once again accounts for a significant share of the total quantity effect. This is particularly true for the lowest market share varieties, in which the store elasticity accounts for three quarters of the aggregate quantity tariff elasticity. Although not shown in Table 3, the magnitude of the quantity per store estimate is also decreasing in market share (this is simply the difference between column (2) and column (3)).

5.3 Discussion

This section provides a brief discussion of the estimates provided here. Specifically, this discussion focuses on three aspects of the heterogeneity estimates described above: (1) these estimates imply a remarkable range of price elasticities across varieties within categories depending on market share; (2) aggregating varieties to the category level and estimating positive pass-through and negative substitution effects masks the fact that this pass-through and substitution are fundamentally occurring two different variety groups within these categories; and (3) the notion that pass-through of any cost shock is increasing in market share is at odds with the existing literature, and we discuss potential mechanisms behind this result.

Implied price elasticities: The estimates from columns (1) and (2) of Table 3 allow for a recovery of implied prices elasticities by dividing the quantity elasticity by the price elasticity. The resulting range of implied price elasticities is remarkable: varieties in the lowest market share bin exhibit a price elasticity of approximately 12, whereas varieties in the highest market share bin exhibit price elasticities of basically zero. From low to high, the vector of implied price elasticities is -11.9, -1.9, -2.5, -1.9, and 0.1.

When calculated as the price elasticity *within* store – that is, the ratio of the quantity per store elasticity to the price elasticity – the resulting vector of elasticities is -3.1, -2.5, -1.2, -0.7, -0.4. These results echo our headline estimates from Section XX: the ability of stores to simply drop affected barcodes may lead to skewed estimates of the relationship between quantity and price tariff elasticities. When estimated as a *within*-store price elasticity, the estimates are more in line with price elasticities one would expect, and are decreasing monotonically in market share.

Separation of pass-through and substitution: A striking feature of Table 3 is the extent to which the price effects and quantity effects of tariffs are separated along the market share distribution. That is, the largest price effects are heavily concentrated within the highest two market share bins. Indeed, the average pass-through rate is 26% for these two bins, which account for 35% of all expenditure on Chinese barcodes in the NielsenIQ data. The remaining 65% of Chinese barcodes, by expenditure, exhibit an average pass-through

estimate of around 9%.

And yet for the quantity estimates, the effects are highly concentrated in the lowest market share varieties. As a partial equilibrium accounting exercise, we can combine the initial distribution of barcodes in Table A.1 and the estimates from Table 3 to calculate the new distribution of varieties across market share bins, post tariff implementation. The lowest market share bin experiences a decrease in total expenditure share of Chinese barcodes from almost 30% pre-tariff to only 8% post-tariff. The largest market share bin experiences an increase in expenditure share from 14% pre-tariff to 25% post-tariff.

Estimates of tariff pass-through and substitution which are unable to measure price and quantity over time within a reliably defined product are thus unable to allocate the price effect of tariffs and the quantity effect of tariffs to separate barcodes, which we have found to be the case here. If calculated as a back-of-the-envelope calculation, this reshuffling of market share mechanically increases the total average pass-through of tariffs into prices, as market share shifts towards varieties with higher price pass-through. We find that while our baseline estimates of tariff pass-through are approximately 15%, incorporating this reshuffling of market share increases the measured "average" tariff pass-through to 19%.

Relationship to literature: The pass-through estimates described here are somewhat at odds with the prevailing literature, and in particular the models of pass-through popularized by Atkeson and Burstein (2008). In these models, low market share firms price at, or near, marginal cost, as mark-ups are increasing in market share. Cost shocks which are common to all firms in the market therefore exhibit full, or close to full, pass-through for these low market share firms. Firms with more significant pre-shock mark-ups, such as those at the high end of the market share distribution, are able to leverage this cost shock to gain market share by passing through less of the shock into prices, and therefore gaining a price advantage over their high pass-through competitors. Thus, cost shock pass-through is *decreasing* in market share.

While the quantity estimates provided in Table 3 are able to match the intuition of these models that large firms may gain market share due to a common cost shock, the observed price elasticities exhibit the opposite pattern of pass-through. We find strong evidence that

pass-through is *increasing* in market share. While we do not, as of yet, have a full model to rationalize these results, it is worth considering the two-sided bargaining model of pass-through described in Alviarez et al. (2023). In our case, the buyers are retailers, and the sellers are producers of barcodes. While low market-share producers may be compelled to pass-through all of the tariff cost shock, this pass-through may be too much for retailers to accept, in particular if they have the outside option of simply dropping the varieties in question.

We find some evidence that retailers do respond by dropping those varieties which one would expect to exhibit the highest pass-through, given the intuition of models such as Atkeson and Burstein (2008). Thus, we leave the mechanisms for future study and future versions of this paper.

6 Conclusion

Despite a substantial literature documenting the economic consequences of the US-China trade war, their remain a number of empirical puzzles. One of these puzzles is the surprising lack of evidence regarding pass-through of tariffs into consumer prices, despite ample evidence of pass-through into prices recorded at the border (via customs data). This paper uses novel data to track the origin country, prices, and units sold at the barcode level across 30,000 U.S. stores before and after the tariffs implemented by the U.S. on Chinese exporters. We find positive and statistically significant tariff pass-through into U.S. prices of approximately 15%, while quantity sold decreased, on average, by over 50% for targeted barcodes. We document a positive relationship between variety-specific market share and pass-through, and a negative relationship between variety-specific market share and the quantity elasticity of tariffs, suggesting that the price effects of these tariffs and the quantity effects acted separately on different portions of the market share distribution.

Future iterations of this paper will study the anti-competitive effects of these tariffs (did prices of non-targeted varieties also increase?) as well as the effect of tariffs on variety entry/exit, and subsequent compositional effects of tariffs on product market characteristics.

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A Appendix: Additional Tables and Figures

This section provides additional tables and figures, as described in the main text.

A.1 Additional Tables

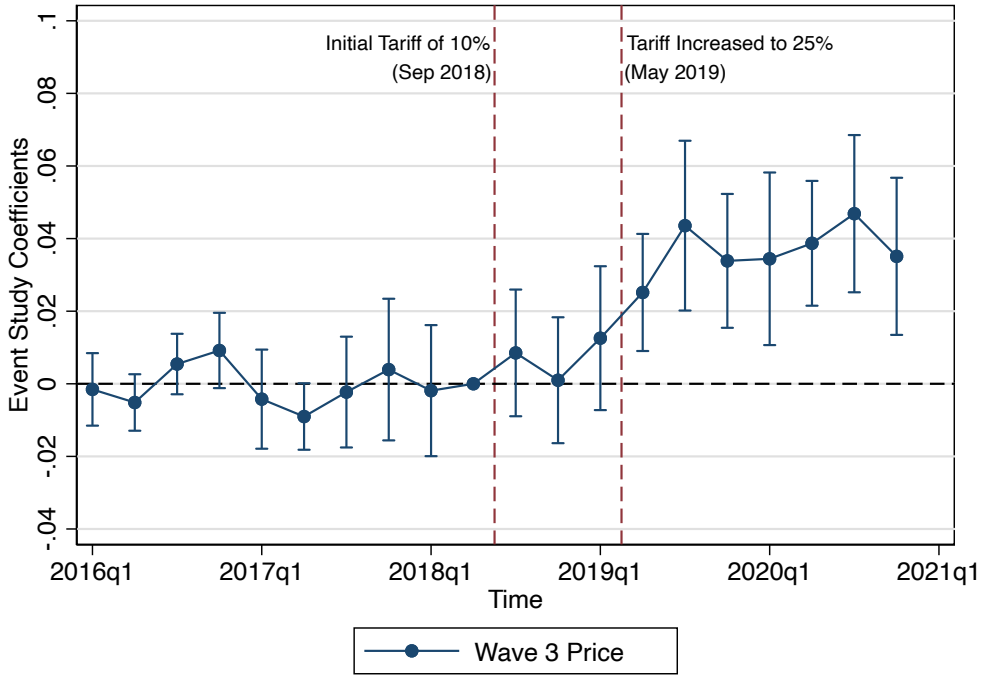
Table A.1: Market Share Bin Summary Statistics

	Market Share Bins				
	(1)	(2)	(3)	(4)	(5)
	$< 0.25\%$	$0.25 - 0.50\%$	$0.50 - 1.00\%$	$1.00 - 2.50\%$	$> 2.50\%$
Share of Products (ALL)	85.7	5.3	3.9	3.0	2.2
Share of Expenditure (ALL)	26.1	15.5	17.4	20.7	20.3
Share of Products (China)	86.6	4.8	3.9	3.0	1.6
Share of Expenditure (China)	29.9	14.7	19.5	21.9	14.0

Notes: This table provides summary statistics regarding the five market share bins analyzed in Table 3. The first two columns provide the distribution of all barcodes, regardless of origin, across market share bins. The second group of columns provides the same distribution but for Chinese barcodes only.

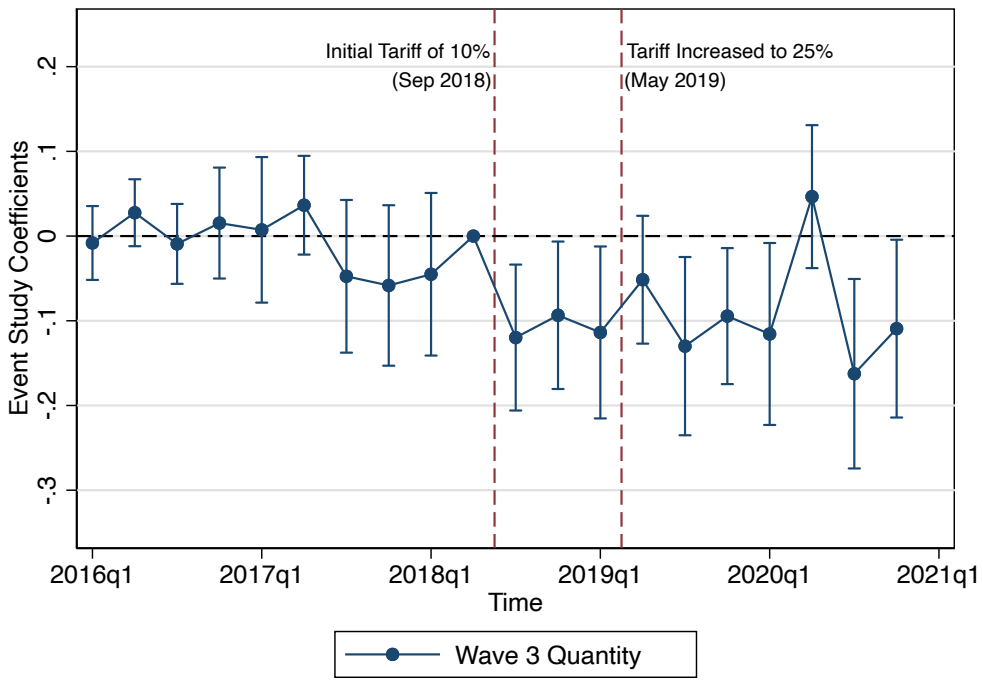
A.2 Additional Figures

Figure A.1: Event Study Estimates: Wave 3 Prices



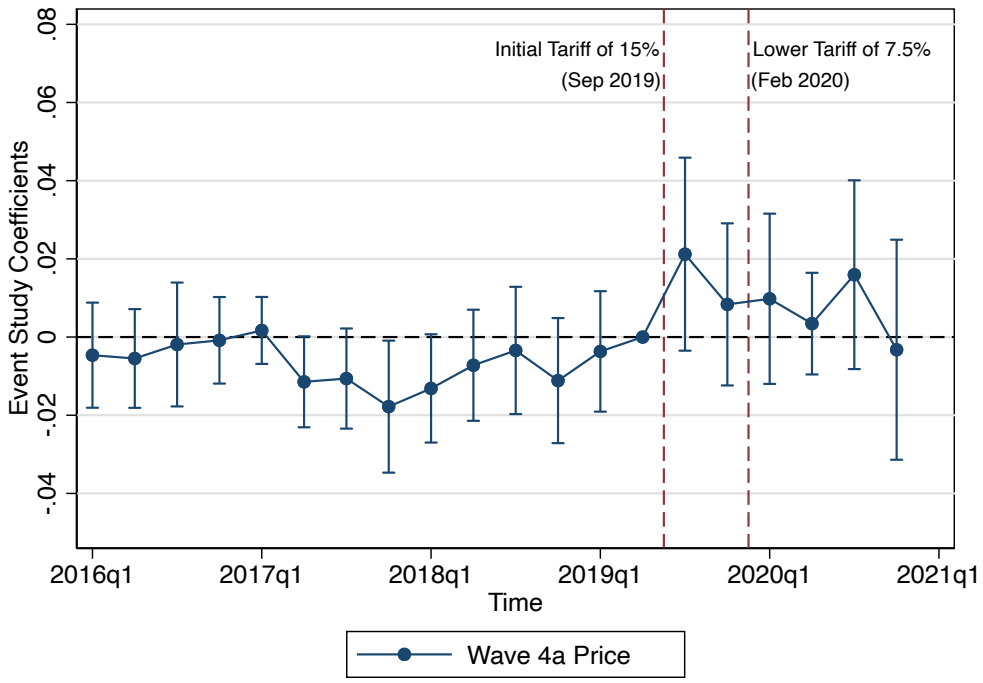
Notes: This figure provides estimates associated with estimating Equation 2. The dependent variable is p_{irt}: prices at the barcode-retailer-month level. All never-tariff categories are included as the control group, whereas the only treated group included are those categories targeted by tariff wave 3. Barcode-retailer, retailer-month, category-month, and country-month fixed effects included. 95% confidence intervals included, with standard errors are clustered at the barcode-retailer level.

Figure A.2: Event Study Estimates: Wave 3 Quantity



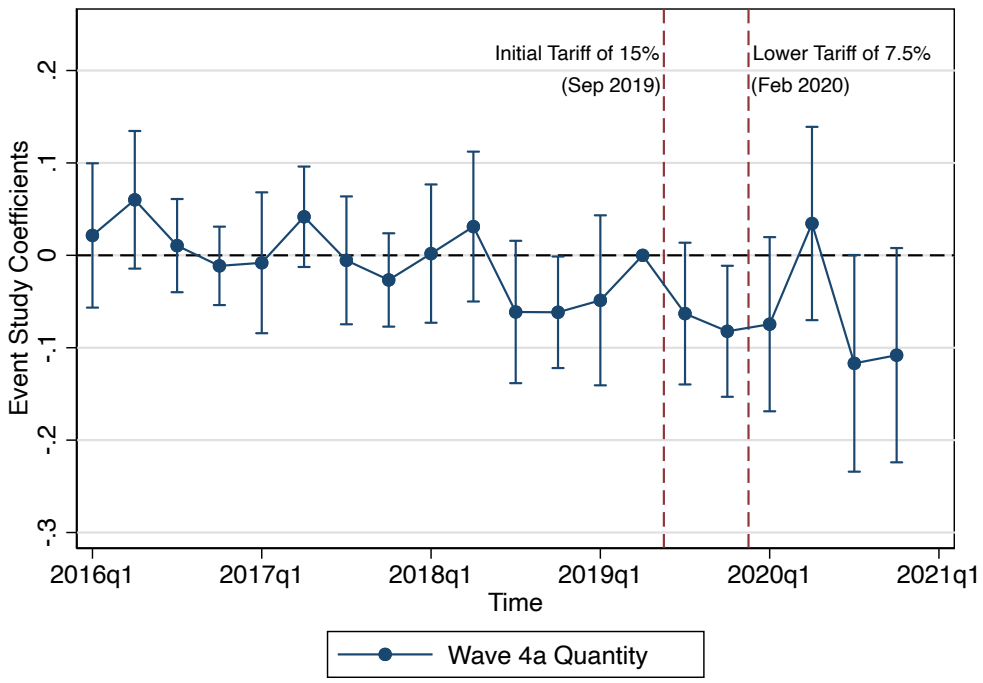
Notes: This figure provides estimates associated with estimating Equation 2. The dependent variable is q_{irt}: quantity sold at the barcode-retailer-month level. All never-tariff categories are included as the control group, whereas the only treated group included are those categories targeted by tariff wave 3. Barcode-retailer, retailer-month, category-month, and country-month fixed effects included. 95% confidence intervals included, with standard errors are clustered at the barcode-retailer level.

Figure A.3: Event Study Estimates: Wave 4a Prices



Notes: This figure provides estimates associated with estimating Equation 2. The dependent variable is p_{irt}: prices at the barcode-retailer-month level. All never-tariff categories are included as the control group, whereas the only treated group included are those categories targeted by tariff wave 4a. Barcode-retailer, retailer-month, category-month, and country-month fixed effects included. 95% confidence intervals included, with standard errors are clustered at the barcode-retailer level.

Figure A.4: Event Study Estimates: Wave 4a Quantity



Notes: This figure provides estimates associated with estimating Equation 2. The dependent variable is q_{irt}: quantity sold at the barcode-retailer-month level. All never-tariff categories are included as the control group, whereas the only treated group included are those categories targeted by tariff wave 4a. Barcode-retailer, retailer-month, category-month, and country-month fixed effects included. 95% confidence intervals included, with standard errors are clustered at the barcode-retailer level.