Tariff Pass-through into Retail Prices: Measurement, Product Turnover, and "Shrink-flation"*

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Abstract

To what extent do import tariffs pass-through into retail prices? Existing estimates for the U.S.-China trade war present a puzzle: pass-through into U.S. border prices is consistently estimated to be complete, yet no evidence exists documenting pass-through into retail prices. This paper combines product country-of-origin data with U.S. scanner data to address this apparent discrepancy. We estimate within-barcode tariff pass-through of 15% via a triple-difference identification strategy. Tariff pass-through into aggregated average unit values, however, is between 33%-54%. This discrepancy is explained by product replacement bias: the predominant mechanism of tariff pass-through in this setting is via product turn-over to barcodes with higher per per unit weight. We leverage our detailed data to highlight the role of "shrink-flation" within this context, such that posted prices are effectively unchanged by import tariffs, while average package size exhibits a negative tariff elasticity. Finally, we compare unit values between customs data and scanner data in order to recover the foreign cost share of U.S. retail goods. Our estimates suggest full pass-through at the border should only manifest as 28% pass-through into retail prices, which we cannot reject. We conclude that tariff pass-through into U.S. retail prices was likely complete.

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

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1 Introduction

Who pays for import tariffs? Basic economic theory suggests that the rate of tariff pass-through - the extent to which the buyer price reflects a changing tariff - is the key metric for quantifying tariff incidence across foreign producers and domestic consumers. Empirical estimates of tariff pass-through, however, are scarce given the remarkable liberalization of trade policy over the past 40 years. The U.S.-China trade war of 2018-2019 therefore offers a unique setting in which to study both the outcomes of this particular policy episode, but also the broader incidence of tariffs across importers and exporters, foreign producers and domestic consumers.

Almost all research in this vein convincingly points to the same finding: U.S. tariffs applied to Chinese exports in 2018-2019 were passed through completely into prices paid by U.S. importers, such that U.S. buyers bore the brunt of President Trump's tariffs on Chinese exports (Amiti et al. 2019; Fajgelbaum et al. 2020; Cavallo et al. 2021). And yet there remains remarkably little evidence for any tariff pass-through into prices faced by U.S. households at U.S. stores.[1] As suggested by Cavallo et al. (2021), it may be that U.S. retailers simply absorbed the entirety of the tariff incidence, but such a result can only be inferred from existing estimates, rather than recovered directly. Even more concerning is a lack of consensus regarding how full pass-through at the border *ought* to manifest in retail prices, given the lack of evidence documenting the foreign cost share of retail goods sold in the U.S. and elsewhere.[2]

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. An important feature of our dataset is the combination of both price and quantity data for detailed product definitions – barcodes – over time, thus allowing for a comparison between estimates of within-barcode tariff pass-through and estimates of tariff pass-through into average unit values. While this distinction may seem innocuous, we provide novel evidence that estimates of tariff pass-through are sensitive to the level of aggregation, which in turn allows us to make sense of discrepancies between estimates of

[1] Cavallo et al. (2021) estimate pass-through into U.S. retailer prices of only 3.5%. See Fajgelbaum and Khandelwal (2022) for more discussion.

[2] As an example, if the cost share of domestic economic activity associated with retail goods, such as intra-national distribution costs and retailing costs (land, labor, etc.), is 50%, than a tariff is only applied to 50% of the final value of the good, as priced at U.S. retailers. Full pass-through at the border would imply only 50% pass-through into retail prices.

pass-through at the border (unit values) versus at the store (product specific).[3]

In our first set of results, we set our level of observation at the barcode-retail chain pair and estimate the price and quantity effects of tariffs using a triple-difference identification strategy. That is, for a specific Chinese barcode of deodorant sold at Walmart, how did the imposition of new tariffs affect the price charged at Walmart stores in the U.S. and the quantity of units sold of this specific barcode? We restrict our analysis to only continuing barcodes, such that our estimates are purged of any endogenous compositional effects. We implement a triple-difference identification strategy in which we control for any shocks which are category-specific or origin country specific, thereby comparing tariff-affected Chinese barcodes to unaffected Chinese barcodes, and comparing the evolution of this differential to the same differential across non-Chinese barcodes. Average tariff pass-through for continuing barcodes is 15.4%.[4] We do not find any evidence of pre-trends or anti-competitive price effects on non-targeted goods, and therefore interpret our findings as causal estimates of tariff pass-through into continuing barcodes.

While 15.4% is larger than the null result found in Cavallo et al. (2021), it remains considerably less than the estimates of full pass-through associated with customs unit values. We evaluate two potential causes of this discrepancy: (1) differing definitions, and measurement, of pass-through into customs prices and store prices, and (2) the extent to which retail prices reflect costs associated with post-tariff activity, such as intra-national distribution costs.

With respect to measurement, customs data generally consist of aggregated average unit values, such as total import expenditure divided by the total quantity of imports, as measured by some normalized unit (kilograms, yards, etc.). Pass-through into store prices, however, is often estimated within specific products. What is often missing from comparisons between these two levels of aggregation are datasets which allow for a direct construction of both levels of measurement: consistent product definitions, product country of origin, and quantity sales data are needed, which is rare when using store-level price data (Flaaen et al. 2020; Cavallo et al. 2021). A unique feature of our dataset is the combination of well-defined products alongside sales, price, and barcode characteristics such as size. We therefore aggregate our scanner data to unit values at the retailer-country-category level which are more reminiscent of what a researcher would observe in customs data. Following from our deodorant example introduced earlier, these unit values are calculated as the average price per unit weight of all barcodes from China sold at all Walmarts in the U.S.

[3]Throughout this analysis, we will be focusing exclusively on tariff waves 3 and 4a associated with the U.S.-China trade war. Waves 1 and 2 primarily targeted goods with poor representation in scanner data, such as intermediates and capital goods. Section 2 provides more detail.

[4]This estimate is robust to excluding 2020 data from our analysis, which may be associated with measurement error introduced by the Covid-19 pandemic.

We then implement a similar triple-difference identification strategy as in our barcode-level analysis. Tariff pass-through into average unit values is 33%, with no evidence of pre-trends. We consider sample restrictions in order to ensure the units of weight are standardized across barcodes within a given retail chain and category, and find that 33% likely represents a lower bound: when we drop all barcodes which do not align in their unit of measurement with the predominant unit of weight associated with that product category, pass-through into unit values increases to 54%. By leveraging the uniquely detailed nature of our data, we provide novel evidence that this discrepancy between pass-through into average prices versus pass-through into product-specific prices is attributable to "shrink-flation": the tariff elasticity of average package size is -0.44 and is distinguishable from zero at 99% confidence levels. We provide an exact decomposition of the unit value tariff elasticity into a component associated with "sticker" prices – prices which are not normalized by weight – and the average weight associated with barcodes sold. Surprisingly, we find a negative, although statistically insignificant, elasticity of sticker prices with respect to tariffs of -0.108. Thus, tariffs lead to higher unit values via a decrease in the denominator – the average weight of packages sold – alongside, if anything, a small negative effect on the posted prices of tariff-affected goods.

Taken together, these estimates provide the first evidence that tariff pass-through into retail prices may occur via "shrinkflation" - a reduction in the size of barcodes sold - as opposed to an increase in consumer-facing prices. Importantly, this result suggests considerable nuance is needed when linking store-level pass-through estimates to those measured at the border. First, aggregated average unit values are not equivalent, nor necessarily comparable, to within-product pass-through when product turnover is the predominant mechanism whereby retailers achieve pass-through. Second, it is imperative that pass-through into store prices is measured using normalized prices, as we find a misleading null effect of tariffs on posted sticker prices. By accounting for this discrepancy in measurement, we document pass-through into U.S. retail prices of at least 33%.

But does this estimate imply that retailers absorbed the remaining 67% of tariff incidence? Not necessarily. A significant share of retail costs occur after tariffs are applied, such as intra-national trade costs and the costs of retailing due to land, labor, and capital employment. Estimates of pass-through into retail prices in fact represent a lower bound on estimates of pass-through into customs data, for the simple reason that the foreign cost share of retail goods is bounded above by unity. In practice, of course, the foreign cost share is likely lower than one, suggesting that pass-through into retail prices must be scaled by this foreign cost share in order to be comparable to pass-through into border prices.

Yet data documenting the foreign cost share of retail goods is scarce. Estimates that do exist tend to place the foreign cost share of retail between 30%-50% (Berger et al. 2012).

While this work is ongoing, we intend to compare customs data unit values at the HS8-country level with the prices recorded in scanner data at similar levels. This ratio of average unit values provides an estimate of the magnitude of the foreign cost share. As validation, we intend to test whether this measure of the foreign cost share is positively correlated with higher tariff pass-through, as theory would predict. That is, within our triple-difference identification strategy, we can interact our estimate of the foreign cost share at the category-country level with tariff changes at the same level of observation. Our null hypothesis is that pass-through should be increasing in the foreign cost share, if our measure of the foreign cost share is indeed relevant.[5]

While this work is still in early stages, our initial estimates suggest a foreign cost share of approximately 28%. This is at the low end of previously documented estimates, although still within the existing range. This estimate is statistically indistinguishable from our preferred pass-through elasticity of 33%, such that tariff pass-through into U.S. retail prices was in fact complete. That is, to the extent that a foreign cost shock could possibly pass through into retail prices, we find that the costs of the import tariff shocks associated with the 2018-2019 U.S. trade war were borne entirely by U.S. consumers, rather than domestic retailers or foreign producers.

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. Flaaen et al. (2020) find pass-through of over 100% for anti-dumping duties applied to all foreign dishwashers, but recover tariff pass-through of approximately 30% when these anti-dumping duties are applied only to China. Our preferred estimate of tariff pass-through is indistinguishable from their China-specific estimate. The closest paper to ours is Cavallo et al. (2021), who also study tariff pass-through into U.S. retail prices. Our analysis crucially benefits from data on both prices and quantities at the barcode level, which allows us to correct for two potential sources of bias in relating retail price pass-through to pass-through at the border.[6]

[5]Note that existing estimates of full pass-through at the border preclude any tariff incidence applying to foreign producers, and we take such estimates as given in our analysis.

[6]See Fajgelbaum and Khandelwal (2022) for a full literature review of the first U.S.-China trade war. Key papers 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.

Specifically, we first document the discrepancy between pass-through into barcode-specific prices and pass-through into aggregated average unit values. We are not the first to suggest that aggregated unit values may behave differently from price series associated with specific goods. Nakamura and Steinsson (2012) argue that product turnover is a common method through which firms increase prices, yet price changes are often measured within the same product over time, in particular for micro-price series associated with international trade. They term this effect "product replacement bias" and argue that de-biased estimates of exchange rate pass-through are twice as high once this effect is accounted for. We recover a similar level of bias, with unit value pass-through estimates also twice as large as pass-through into product-specific prices.[7] Producers and/or retailers may perceive product replacement as a mechanism for increasing prices which generates less negative sentiment among consumers (Rotemberg 2005; Nakamura and Steinsson 2011), and a growing literature suggests that "shrink-flation" may be a particularly common method by which firms achieve higher prices when replacing products (Evangelidis 2024; Chalioti and Serfes 2024).

Finally, we contribute to the literature quantifying the foreign cost share of domestic retail goods. Berger et al. (2012) estimate a range for U.S. retail goods of between 30%-50%, noting that that these estimates are between 10 and 20 percentage points lower than most existing estimates (Burstein et al. 2003; Devereux et al. 2003; Anderson and Van Wincoop 2004; Goldberg and Campa 2010). Our current estimate of 28% therefore lies at the lower end of this range. Future work will continue to refine this estimate and to explore heterogeneity across categories and origin countries, which Berger et al. (2012) suggest is significant.

Finally, by studying the endogenous response of retailers to tariffs, 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).

Section 2 describes our data. Section 3 provides barcode-specific estimates of pass-through, while Section 4 provides estimates of pass-through into average unit values. Section 5 remains a work in progress, in which we intend to estimate the foreign cost share of retail prices, thereby allowing for a full decomposition of tariff incidence across consumers and retailers. Section 6 concludes.

[7] "Product replacement bias" is distinct from the endogenous quality response of firms to changes in trade costs, as discussed in Metzler (1949) and documented by Ludema and Yu (2016); Chen and Juvenal (2016); Freitag and Lein (2023). Similarly, while product entry should reduce the real price index, as in Feenstra (1994) and Broda and Weinstein (2006), the "product replacement bias" is instead concerned with the role of product replacement in the measurement of prices. That is, a counterfactual price change would have occurred within a given product, but for the use of product replacement as a means of achieving this objective.

2 Data

We bring together a number of data sources for the empirical analysis of this paper: barcode-level price and expenditure from NielsenIQ Retail Scanner Data, barcode-level country-of-origin data purchased from Label Insight, barcode-level country-of-origin data scraped from the website of a large U.S. retailer, tariff data at the eight-digit Harmonized System (HS) level from the U.S. International Trade Commission (USITC), firm identifiers from GS1, and a concordance between Nielsen product modules and HS-10 digit codes.[8]

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 2017-20. 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, where a retailer denotes a retail chain – such as Walmart – within which all store sales are aggregated. To abstract 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. The same Coca-Cola package sold at Target would constitute an additional observation, as would a Coca-Cola package of a difference size sold at Walmart.

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 our scanner data with two separate data sources. First, we use a proprietary dataset purchased from Label Insight, a private firm specializing in the provision of detailed

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

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 35% 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 A.1, the distribution across Nielsen departments (both in terms of number of UPC codes and expenditure) looks similar for the matched and broader samples. 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.[9]

2.3 Tariff Data

Figure A.2 shows the weighted average tariff that the U.S. Government 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.[10] 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 7 ppt, compared to a pre-2018 baseline average tariff rate of around 3%.

There were four waves of tariff changes associated with the 2018-2019 trade war. Figure A.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, thus generating a substantial volume of imports as our control group. 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 exclusively on the tariff changes associated with waves 3 and 4a.

As shown in Figure A.3, the wave 3 tariffs experienced two increases: from 2.5% to 12.5% in September 2018, and a further increase to 27.5% in May 2019. Wave 4a categories experienced 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 provide results using all categories and separately for each tariff wave. We also explore estimates both

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

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

including and excluding data from 2020.

3 Pass-through into Product-Specific Prices

This section provides estimates associated with tariff pass-through and substitution within barcodes. The unit of observation throughout is a barcode-retailer pair, which is similar to the data structure used by Flaaen et al. (2020) and Cavallo et al. (2021).

3.1 Empirical Model

We implement a triple-difference identification strategy at the barcode-retailer level. That is, we compare barcodes produced in China to non-Chinese goods within the same product category and compare this difference across targeted and non-targeted categories before and after tariffs were implemented, all within the same retail chain. A key feature of the dataset used here is consistent and well-defined products – barcodes – such that the tariff elasticities we estimate are within the same barcode for both prices and quantities.

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

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

α_{irt} denotes a vector 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 (α_{ct}). Finally, we control for country-period fixed effects, such that any exchange rate shocks or demand shocks which are origin-specific are captured by α_{jt}.

The vector $\gamma_{i,q(t)}$ denotes seasonality controls which are specific to tariff-targeted categories. In analyzing our raw price and sales data, we find 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.[11] 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.

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

We focus on two primary outcomes of interest at the barcode-retailer pair level: price and total quantity of units sold. Given that this specification can be interpreted as a triple-difference estimator, we employ an event study design to check for pre-trends by applying OLS to Equation 2 and plotting the estimate vector β_γ.

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

T denotes the date of the first tariff change. In generating event study figures, we separate categories associated with tariff wave 3 and wave 4a into separate analyses, such that the control group in each case is the never-treated set of products.

3.2 Results

We first provide estimates of barcode-level pass-through for a balanced panel of barcodes. That is, we omit all barcodes which enter or exit the sample during the tariff period, and we restrict our analysis to those barcodes which were present in 2017 (prior to tariff implementation). Table 1 provides these estimates.

Columns (1)-(3) provide estimates associated with price as the dependent variable, such that these estimates can be interpreted directly as pass-through estimates: $\beta = 0.141$ implies pass-through of tariffs into retail prices of 14.1%. Column (1) provides our baseline estimate, as outlined in Equation 1, with all years from 2017-2020 included. Column (2) separately estimates pass-through for products associated with tariff wave 3 and tariff wave 4a, respectively. Finally, column (3) drops 2020 in order to reduce the noise associated with the Covid-19 pandemic, which limits the sample to only categories affected by tariff wave

[11] 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 $\Gamma_i = 1$.

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
$\log(1+\tau)$	0.141***			-0.171		
	(0.032)			(0.143)		
$\log(1+\tau) \times$ Wave 3		0.142***	0.159***		-0.171	-0.254
		(0.032)	(0.036)		(0.144)	(0.166)
$\log(1+\tau) \times$ Wave 4		0.109*			-0.163	
		(0.059)			(0.220)	
Wave 3 only			✓			✓
Sample			≤2019			≤2019
Fixed Effects (α_{irt})	✓	✓	✓	✓	✓	✓
R^2	1.00	1.00	1.00	0.97	0.97	0.98
Observations	23290527	23290527	9,979,736	23290527	23290527	9,979,736

*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 two-way at the category-country and month level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.*

3.[12] Columns (4)-(6) provide the same estimates but with quantity sold as the dependent variable.

We estimate average tariff pass-through of 14.1%, when averaged across both tariff waves and including the year 2020. This estimate is significantly distinguishable from zero at levels of 99%. While Wave 3 exhibits higher pass-through than Wave 4 (14.2% versus 10.9%), this may be due to measurement error associated with the Covid-19 pandemic: when 2020 is omitted and only wave 3 categories are included, the estimated pass-through coefficient increases to 15.9%.

Reassuringly, we find no evidence of pre-trends associated with the price pass-through estimates described in Table 1. Since the two tariff waves – wave 3 and wave 4a – were implemented at different times, we estimate two separate event study models, with Figure A.4 and Figure A.6 in Appendix A.2 illustrating these event study plots. In both cases, there is no evidence of pre-trends in prices prior to tariff implementation, and the post-tariff estimates suggest an immediate and sustained differential in prices. Indeed, the reduction in tariffs associated with wave 4a from 15% to 7.5% in early 2020 coincides with a decrease in the gap in prices between tariff-targeted and untargeted Chinese barcodes.

Figure A.5 and Figure A.7 provide the same event study analysis, but with a focus

[12]Tariff wave 4a was implemented in the Fall of 2019, thus limiting the post-Covid sample available for estimation. Wave 4a also experienced a decline in the applied tariff rate from 15% to 7.5% after six months of implementation, which likely also introduces noise into our estimates.

on quantity sold. In this case, there is some evidence of downward trends prior to tariff implementation, and a less clear effect of tariffs on any sustained decrease in quantities sold. These event studies mirror the lack of precision in our triple-difference estimates from Table 1: we estimate a quantity tariff elasticity of -0.171 for our full sample, and -0.254 when limiting our analysis to wave 3 only, but both estimates are insignificant at standard confidence levels.

These results represent the first estimates to date of positive, and statistically significant, pass-through into U.S. store prices associated with the tariffs levied by the first 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. We return to discussing the discrepancy between their estimates and ours in the following paragraphs. Our headline estimates suggest a price elasticity of 1.21, which increases to 1.60 when only wave 3 is considered.[13] Both estimates are within the range one would expect, given existing estimates of price elasticities found in the grocery sector demand estimation literature.[14]

3.3 Extensions, Robustness, and Discussion

This section provides a number of extensions, robustness checks, and a discussion which motivates our analysis at an aggregation higher than the barcode, which we turn to in Section 4.

Anti-Competitive Effects: One potential concern associated with our triple-difference identification strategy is the assumption that products which are not specifically targeted by tariffs constitute a reasonable control group. Any model of strategic pricing would suggest that tariffs on Chinese varieties might induce an increase in markups for competing varieties from other origin countries. We test this effect directly using a differences-in-differences identification strategy, and comparing the effect of tariffs on the price of non-targeted products within tariff categories to products in non-tariff categories. Specifically, we estimate the following empirical model:

$$\ln(y_{irt}) = \beta \ln(1 + \tau_{ct}^{cn}) + \alpha_{ir} + \alpha_{rt} + \alpha_{jt} + \alpha_{g(c)t} + \epsilon_{irt} \tag{3}$$

[13] By "price elasticity", we refer to the implied demand elasticity associated with the quantity and price tariff elasticity, such that $-(-0.171/0.141) = 1.21$.

[14] Faber and Fally (2021) recover demand elasticity estimates from scanner data distributed around two.

where τ_{ct}^{cn} denotes the tariff applied to Chinese varieties within category c, which is now the explanatory variable for all non-Chinese varieties within that same category. All other fixed effects remain the same, other than the category-time fixed effects α_{ct}. Note that such fixed effects would entirely absorb the tariff variation across categories, so we include fixed effects at a higher level of category classification, $\alpha_{g(c)t}$, where $g(c)$ denotes ten departments, within which all product categories are exhaustively classified.[15]

Table A.1 highlights the lack of anti-competitive effects present in our data. Not only do we recover price effects that are indistinguishable from zero at standard confidence levels, we also recover small estimates in terms of economic magnitude, with reassuringly precise confidence intervals. It should be noted that in a similar exercise, Cavallo et al. (2021) also find little evidence for anti-competitive behavior within consumer goods. However, within consumer packaged goods, China's expenditure share in the U.S. is smaller than in many other export markets, with shares that are typically less than 5% of all sales. Thus, it is not immediately clear that the combination of low market shares and (relatively) small tariff changes would lead to observable anti-competitive behavior.

Unbalanced Panel: Our headline estimates are associated with a subsample of continuing barcodes: those barcodes present throughout the entirety of our sample. Interestingly, when we estimate the same elasticities but for an unbalanced panel of barcodes – that is, the entire set of observations of all barcode-retailer pairs – we recover a precisely zero estimate of pass-through intro prices alongside a much stronger substitution effect. These estimates can be found in Table A.2.

With respect to tariff pass-through into prices, we therefore find evidence of zero pass-through for varieties which entered or exited the market during our sample period. The quantity effects, however, suggest that varieties which did not remain in the sample exhibited a far stronger quantity response to tariffs than those which continued: we estimate a substitution elasticity of -0.590 for the unbalanced panel versus -0.171 for the balanced panel.

This discrepancy is not due to compositional differences between the balanced and unbalanced panel, as all regressions include barcode-retailer level fixed effects. Instead, these estimates suggest a differential response to tariffs associated with barcodes which eventually exited the market and those that remained. The quantity estimates are perhaps unsurprising: conditional on a barcode eventually exiting the market, it is intuitive that an exiting barcode would exhibit greater substitution prior to exit. The lack of price effects is surprising and remains a focus of future work in this project. One possibility is that stores which

[15] We drop all barcodes from China in this specification thereby eliminating the need for seasonality controls, which are specific to tariff-targeted products.

know they are ultimately going to discontinue their stocking relationship with certain tariff-affected barcodes do not pass-through a tariff in order to maintain sales and clear inventory. As of now, however, this mechanism is purely speculative.

Comparison with Cavallo et al. (2021): The only existing scanner estimates of pass-through into U.S. prices during the 2018-2019 trade war are from Cavallo et al. (2021), who find no evidence for tariff pass-through into U.S. retail prices. While our dataset differs from theirs, we also employ a slightly different identification strategy: we opt for a triple-difference identification strategy via country-period fixed effects whereas Cavallo et al. (2021) include country-period controls such as exchange rates and producer price indices directly. Still, we find similar levels of tariff pass-through when we adopt their empirical strategy to our data setting, suggesting that the discrepancy lies primarily in data used and potentially also in the mapping between product categories and tariff codes: any error in mapping scanner product categories to tariff codes would lead to attenuation bias, thus biasing estimates of tariff pass-through towards zero. Appendix B.1 provides more details regarding this comparison between our methodology and Cavallo et al. (2021), as well as results discussed here.

Extensive Margin: Table A.3 provides estimates associated with a modification of Equation 1. Specifically, we define $E_{irt} = 1$ as an indicator variable for whether barcode i exhibits non-zero sales at retailer r in time t, and we expand our dataset to cover a balanced panel across all barcode-retailer pairs. When estimating Equation 1 with E_{irt} as the dependent variable, we recover the effect of tariffs on net exit, or the net probability of a given barcode being present at a given retail chain.[16] Columns (1) to (3) in Table A.3 highlight the negative extensive margin effects of tariffs, with a 10% tariff increase raising the probability of exit within a given month by 1.7 percentage points. Columns (4) to (6) provide a similar analysis but with the dependent variable equal to one if the given time period is between the first and last observed sale of barcode i at retailer r, with estimates that are less precise, but still negative. We find much stronger negative extensive margin tariff elasticities when we aggregate to the barcode level, as opposed to the barcode-retailer pair, as shown in Table A.4.

Discussion: While this paper is the first to document within-product tariff pass-through into U.S. grocery prices, it seems clear that such estimates do not necessarily generalize to the entire consumption basket. After all, continuing barcodes are an endogenously selected

[16]Note that we maintain the barcode-retailer fixed effects, which effectively control for the amount of time a given barcode has been present at a given retailer

sample, as evidenced by our finding of significant tariff effects on product exit. Such estimates also make surprisingly little progress in helping us understand the discrepancy between estimates of complete pass-through at the border and muted pass-through into U.S. stores: taken at face value, we are still left with the unsatisfying result that retailers absorb 85% of tariff incidence. In the next section, we show that pass-through into average prices, or unit values, allows for a more direct comparison between store prices and customs data, as customs data generally record unit values rather than product-specific prices. In doing so, we provide evidence that tariff pass-through was at least 33%, and potentially as high as 54%.

4 Pass-through into Aggregated Unit Values

This section provides estimates of tariff pass-through and substitution at the level of a category-country-retail chain triad.[17] This level of aggregation is useful in that it provides a closer link between store-level prices and those observed in customs data, which are often average unit values with no clear product delineation. We show that pass-through into average prices is significantly higher than pass-through into barcode-specific prices, such that true tariff pass-through into retail prices is 33%. We provide evidence that this discrepancy (33% versus 15%) is due to "shrinkflation": producers (and/or retailers) concentrating sales in smaller barcodes while maintaining constant sticker prices, thereby increasing average price per unit weight.[18]

4.1 Empirical Model

For each category-country-retailer triad jcr we calculate four separate dependent variables: average price per unit weight (or unit value), total quantity sold, average sticker price, and average weight (size) of barcodes sold. When aggregating, we use sales quantity weights to construct averages.

We calculate all variables for both the balanced panel used in our previous estimates and for an unbalanced panel of all raw barcode-retailer observations. Recall that our balanced panel constitutes barcodes exhibiting non-zero sales throughout our sample, and therefore abstracts from entry and exit. The unbalanced panel allows for the possibility of entry

[17] For example: pass-through into the average price of deodorant produced in China sold at Walmart. Estimates in Section 3, by comparison, recover pass-through into the price of a specific barcode of deodorant produced in China and sold at Walmart.

[18] By "sticker price", we refer to the non-normalized price, such that total expenditure is divided by the number of units sold, rather than the weight of units sold.

and exit. At this aggregated level of country-category-retailer triads, we employ a similar triple-difference identification strategy as in the barcode-level analysis earlier. Specifically, we recover β by applying OLS to the following estimating equation for dependent variable y_{jcrt}:

$$\ln y_{jcrt} = \beta \ln(1 + \tau_{jct}) + \alpha_{jcrt} + \gamma_{jc,q(t)} + \epsilon_{jcrt} \tag{4}$$

where α_{jcrt} is a vector of fixed effects, such that

$$\alpha_{jcrt} = \alpha_{jcr} + \alpha_{rt} + \alpha_{ct} + \alpha_{jt}$$

We include fixed effects that mimic the barcode-level analysis: a constant fixed effect at the unit level (retailer-country-category jcr), and fixed effects to capture shocks at the retailer, category, and origin country level. We include the same seasonality controls $\gamma_{jc,q(t)}$ as in Equation 1. In order to compare the unbalanced panel estimates with the balanced panel estimates, we restrict our sample to the set of rjc triads present for the balanced panel of barcodes. Thus, the number of observations are identical for the balanced and unbalanced panel: instead, “balanced" and “unbalanced" refer to the underlying set of barcodes used to construct these aggregated variables.

We define p_{irt} as the raw sticker price, and q_{irt} as the raw quantity (as in the number of packages bought), so that expenditure are $x_{irt} = p_{irt}q_{irt}$. Let w_{ir} denote the weight per package (e.g. 0.5kg per unit). The weight of the same barcode does not change over time, as weight changes would result in a new barcode. The variable w_{ir} therefore does not have a t subscript. The weight-adjusted quantity – our preferred measure of quantity sold – is then $\tilde{q}_{irt} = q_{irt}w_{ir}$. The adjusted price – our preferred measure of pass-through – is now measured as price per kg ($\tilde{p}_{irt} = p_{irt}/w_{ir}$), sch that $x_{irt} = \tilde{p}_{irt}\tilde{q}_{irt}$. We can therefore construct a measure of aggregated unit values which is given by $uv_{jcrt} = x_{jctr}/\tilde{q}_{jcrt}$. We provide an exact decomposition of this unit value into two components, an average sticker price and an average weight per unit sold:

$$uv_{jcrt} = \frac{x_{jctr}}{q_{jcrt}} \frac{q_{jcrt}}{\tilde{q}_{jcrt}} = \left(\sum_i \frac{q_{irt}}{q_{jcrt}} p_{irt} \right) \times \left(\sum_i \frac{q_{irt}}{q_{jcrt}} w_{ir} \right)^{-1}$$

The first term captures the weighted average sticker price, while the second captures the weighted average weight. The weights come from unadjusted (raw) quantities, which is simply the number of packages sold of a given barcode. While it may not seem intuitive to weight by the number of units sold – as opposed to weighting by the total quantity of weight sold – this decomposition provides an exact breakdown of the effect of tariffs on average unit

values into two readily measurable components. We therefore estimate $d \ln uv_{jcrt} / d \ln \tau_{jct}$ and the same elasticity for both component: the average sticker price facing consumers on store shelves and the average weight of barcodes sold.

4.2 Results

Table 2 provides estimates for each of the four dependent variables introduced earlier, as well as for the balanced and unbalanced panel approaches to constructing average and aggregate quantities. Columns (1) and (2) provide pass-through estimates into average unit values, where unit values are constructed as the average price per unit weight of barcodes sold. We find pass-through into average prices for the balanced panel of 9.1%, which is reassuringly similar to the product-specific pass-through of 15% discussed earlier.[19]

Interestingly, pass-through into average price per unit weight for the unbalanced panel is much larger than the balanced panel, at 32.9%. This estimate is distinguishable from zero at levels of 10%. Figure A.8 compares an event study analysis of these two estimates (balanced and unbalanced) to confirm no pre-trends associated with the unbalanced panel alongside a sustained differential increase in prices post-tariff. This estimate is even more interesting given that we found zero pass-through in the unbalanced panel into barcode-specific prices (see Section 3.2). Thus, the discrepancy between Columns (1) and (2) must be due to a shift in composition: either low price per unit weight barcodes exit in response to a tariff or high price per unit weight barcodes enter (or both).[20]

Understanding the mechanism behind this result is crucial, as there is no *a priori* reason to believe that pass-through into aggregated unit values ought to differ from pass-through into barcode specific prices, and indeed such comparisons have so far been the only comparisons made between pass-through at the border and pass-through into U.S. retail prices (Cavallo et al. 2021). We consider the possibility of "shrink-flation" as a mechanism through which pass-through into average unit values is achieved by retailers. That is, we test whether the turnover of barcodes over from existing stock to smaller, yet similarly priced, alternatives may be a method of passing through tariffs to consumers without facing consumer backlash. For the same reason that it is difficult for a researcher to calculate pass-through into entering products - there is no pre-tariff counterfactual price of the variety in question – so too may

[19] Note that we wouldn't expect this estimates to be identical to the product-specific pass-through estimates in Section 3.2, as pass-through into average prices depends on the distribution of pass-through across barcodes according to both market share and initial price.

[20] While the quantity effects are larger for the unbalanced panel, as one would expect, these estimates are ultimately fairly noisy. This may reflect a potential pre-trend in the quantity sold of tariff-affected products associated with wave 4a, as well as the fairly quick reduction in tariff levels associated with this wave after implementation. See Figure A.9 for event study figures.

Table 2: Category-Level Pass-through and Compositional Effects

	(1) Log Price	(2) Log Price	(3) Log Quantity	(4) Log Quantity	(5) Log Price	(6) Log Price	(7) Log Weight	(8) Log Weight
$\log(1+\tau)$	0.086*	0.327*	-0.151	-0.259	0.060	-0.108	-0.026	-0.435**
	(0.045)	(0.180)	(0.174)	(0.395)	(0.038)	(0.096)	(0.039)	(0.185)
Balanced	✓		✓		✓		✓	
Unbalanced		✓		✓		✓		✓
Price per weight	✓	✓						
Raw sticker price					✓	✓		
R^2	1	1	1	1	1	1	1	1
Observations	2,705,306	2,705,306	2,705,306	2,705,306	2,705,306	2,705,306	2,705,306	2,705,306

*Notes: This table provides estimates of β from applying OLS to Equation 4. All models include fixed effects by country-category-retailer, retailer-month, category-month, and country-month. From left to right, dependent variables are: average price per unit weight, total quantity sold (in units of weight), average sticker price (not per unit weight), and the average weight of barcodes sold. All averages are calculated using quantity sales weights. Columns (1), (3), (5), and (7) construct variables using the balanced panel of continuing barcodes, while Columns (2), (4), (6), and (8) use the raw unbalanced panel to construct averages. Standard errors are clustered two-way at the category-country and month level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.*

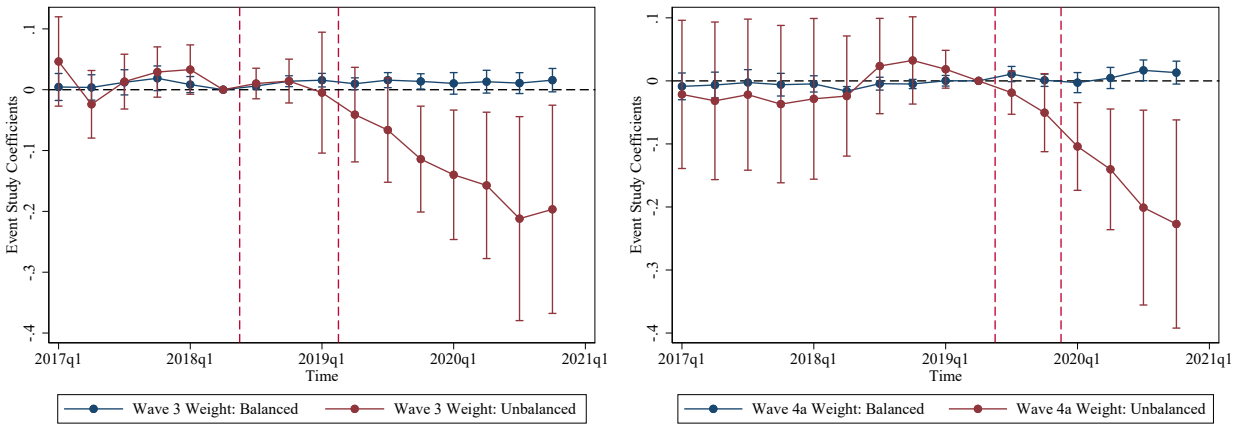
consumers struggle to ascertain exactly how much prices have increased in response to a tariff when faced with entirely "new" products. In the extreme case of an entering barcode simply replacing an otherwise identical exiting barcode, save for a higher price, this would clearly constitute welfare-relevant pass-through: the post-tariff price of the same basket of goods has increased.

Columns (5) and (6) therefore provide estimates of the pass-through of tariffs into the average sticker price, as derived earlier, for both the balanced and unbalanced underlying set of barcodes. These results establish that consumer-facing prices are unaffected by tariffs for the unbalanced panel of barcodes. Interestingly, our estimate of 32.7% pass-through into average unit values is associated with, if anything, a negative effect of tariffs on posted sticker prices. The elasticity in this case is -10.8%, although this estiamte is insignificant at traditional levels of confidence. Figure A.10 provides the event study analysis associated with these estimates, which confirm a lack of pre-trends and a lack of any sustained post-tariff change in sticker prices.

Columns (7) and (8) provide the mechanism underlying this seemingly contradictory result: the average weight of barcodes sold in the unbalanced panel exhibits a strong negative response to tariff implementation. For the balanced panel, sales-weighted average quantities are unaffected by tariffs, whereas the unbalanced panel average barcode weight exhibits a tariff elasticity of -0.435, which is statistically distinguishable from zero at confidence levels of 95%. Figure 1 provides the event study associated with this analysis, which confirms both a lack of pre-trends and a strong, negative effect of tariffs on average weights.

As discussed in our decomposition exercise earlier, we would expect the difference of the

Figure 1: Event Study Estimates for Category Average Weight Effects



Notes: This figure provides estimates associated with an event study design at the aggregated country-category-retailer level. All models include fixed effects by country-category-retailer, retailer-month, category-month, and country-month. The dependent variable is $\bar{w}_{jcrt}$: the quantity-weighted average weight of barcodes sold. Left panel: all never-tariff categories are included as the control group, whereas the only treated group included are those categories targeted by tariff wave 3. Right Panel: never-tariff categories are control but only tariff wave 4a categories are treated. Vertical lines denote tariff changes. The red series uses the unbalanced panel to calculate average prices, the blue series uses the balanced panel to calculate average prices. 95% confidence intervals included, with standard errors are clustered at the category-retailer-pair level.

sticker price tariff elasticity and the average weight elasticity of tariffs to equal the tariff pass-through elasticity into average price per unit weight, which is validated in this case by the estimates presented in Table 2. To our knowledge, these estimates are the first to suggest that "shrink-flation" – the turn-over of products to similarly priced but smaller alternatives – may have been the dominant mechanism through which tariffs were passed through to consumers during the U.S.-China trade was of 2018-2019. Crucially, these estimates preclude the usefulness of estimating pass-through into the price of a single, continuing, product: it is the turnover of products which allows producers/retailers to pass-through tariffs into consumer prices.

4.3 Robustness and Unit Comparability

Our ability to measure the tariff elasticity of average product size depends crucially on accurately measuring product sizes, and ensuring that these measurements are comparable across products. This is particularly crucial given the narrative of results described in this section: if measurement error exists in comparing barcodes sizes over time, such measurement error could bias our estimates of pass-through into average sizes and, crucially, pass-through into average unit values. A natural source of measurement error lies in the correspondences used to compare the size of barcodes measured in differing units (such as kilograms versus

ounces, for example). In general, such correspondences are easy to implement, and we construct normalized sizes within categories.

However, a number of barcodes are simply measured as "counts". For example, a box of tea bags may simply be recorded as consisting of one "count" of tea bags. This is worrisome from the perspective of measuring changes in average sizes over time of barcodes sold, as it is not immediate clear whether the "counts" in question are comparable across barcodes, even within narrow product categories.

We therefore implement two data restrictions in order to rule out the possibility that the estimates presented here are driven by measurement error, rather than representing true tariff elasticities. First, we drop all barcodes which are measured in a unit which is not the dominant unit associated with barcodes of the same retailer-category pair. Specifically, we calculate for each category-retailer pair in 2017 the unit of measurement which represents the greatest share of expenditure and we drop all barcodes within this category-retailer pair associated with all other units of measure. As an example, if deodorants sold at Walmart are predominantly measured in ounces, except for a single barcode which is measured as a "count", we drop this outlier barcode when calculating average prices and weights. Table A.5 provides estimates for this data restriction. In this case, our estimate of pass-through into unit values increases in magnitude to 0.539, suggesting pass-through of 54%. In this case, sticker prices are effectively unchanged, yielding a pass-through estimate of -0.016, with standard errors of 0.093. Pass-through into average product size exhibits an elasticity of -0.555, which is distinguishable from zero at 99% confidence levels.

Table A.6 provides estimates associated with a similar data restriction except in this case we further drop all retailer-category pairs for which the unit of measure is a "count". That is, while Table A.5 allowed for comparisons within retailer-category pairs for which "counts" were the dominant unit of measure, Table A.6 provides a more restrictive requirement: only barcodes associated with the dominant unit of measure are used to construct averages, and only retailer-category pairs with readily comparable units of measure are included. Naturally, our sample size decreases by about 25% when compared to our baseline unit value estimates in Table 2. Thus, our estimate of tariff pass-through into unit values of 40% is not significant at standard confidence levels.[21] However the same qualitative story emerges: we estimate a tariff elasticity of average barcode size of -0.528, which is distinguishable from zero at levels of 95%.

Finally, Table A.7 provides estimates of pass-through into unit values at a more disaggregated level: the firm-retailer-category-country level. In this case, we make use of our firm identifiers at the barcode level to construct aggregates within firms. For example, this could

[21] Indeed the p-value associated with this estimate is precisely $p = 0.10$.

be the average unit value of deodorants sold at Walmart, where all deodorants within a given observation are produced by “Old Spice" and produced in China. We make use of the same fixed effects, except for the inclusion of level fixed effects at the firm-category-country-retailer level, thereby ruling out compositional effects of tariffs across firms. We again find estimates of pass-through into unit values that are approximately three times larger than equivalent estimates for the unbalanced panel, with a pass-through estimate of 0.414, significant at 95% confidence levels. We again find evidence for “shrink-flation", although these estimates are marginally insignificant at standard confidence levels.[22] Table A.8 repeats this exercise and finds almost identical estimates for the data subsample discussed above, in which all barcodes within a given level of observation have identical units of measure.

Taken together, these estimates provide the first evidence that tariff pass-through into retail prices may occur via “shrinkflation" - a reduction in size of barcodes sold - as opposed to an increase in consumer-facing prices. Importantly, this result suggests considerable nuance is needed when linking store-level pass-through estimates to those measured at the border. First, aggregated average unit values are not equivalent to within-product pass-through when product turnover is in fact a mechanism through which retailers achieve pass-through. Second, it is imperative that one measures pass-through into normalized prices as the sticker price, in this instance, does not respond to tariffs.

We therefore argue that tariff pass-through into retail prices occurred via both an increase in prices of continuing products and a replacement of existing products with smaller varieties of identical sticker price. Taken together, this section finds evidence that true pass-through into U.S. stores was likely 33%.

5 The Foreign Cost Share of Retail Imports

Thus far, this paper has provided the first evidence of a positive tariff pass-through into U.S. retail prices associated with the 2018-2019 U.S.-China trade war. Even our largest estimates, however, of around 50% pass-through, still fall well short of the complete pass-through documented at the border. We now turn to the possibility that low transmission of tariffs into consumer goods prices might be the result of a low foreign cost share of U.S. retail sales, such that complete pass-through at the border manifests in U.S. retail prices as the share of foreign costs associated with the final sale price of imported goods.

We define the foreign cost share as the ratio of the pre-tariff border price over the retail price. To see why this share may be important, consider a product that is imported at a

[22] We recover a within-firm average weight elasticity of -0.306, with standard errors of 0.218.

price of $3 per unit, but sold at U.S. retail stores for $12. The difference between the two prices reflects costs, and/or mark-ups, which are associated with economic activity after tariffs have been applied. This wedge might constitute activities such as warehousing, intra-national distribution costs, retailings costs such as land and labor, as well as mark-ups earned by the retailer. We refer to this difference as the distribution wedge. Suppose further that the import tariff is perfectly passed through to the border price, while the distribution wedge remains constant at $9. A 10% tariff would then increase the border price to $3.30, and the retail price to $12.30. That is, there is perfect pass-through in levels (both prices increase by $0.30), but not in logs (the border price increases by 10%, while the retail price by only 2.5%).[23] In the special case discussed here, the foreign cost share of U.S. retail goods would in fact constitute the tariff pass-through into retail prices, assuming pass-through into border prices is complete. By extension, the foreign cost share is crucial for understanding who ultimately pays for import tariffs. Even though the estimated pass-through in this example is only 25%, consumers pay for the entire tariff increase, as retail margins stay fixed. Yet data on the foreign cost share are hard to come by. Recent estimates by Berger et al. (2012) place the foreign cost share of retail between 30%-50%.

While we do not have data on the border prices of individual barcodes, we try to make progress by comparing category-origin-level unit values between retail and customs data. We define the foreign cost share as the ratio of pre-tariff border prices and retail prices. Since the US computed tariff duties using FOB prices, we use the HS10 customs valuation unit values by country of origin, as opposed to CIF unit values which include international transport and insurance. We then try to harmonize as much as possible quantity units of measurement in both the scanner and the customs data. Some unit values cannot be compared across the two datasets, for instance if the unit in the scanner data is simply a "count", but it is measured in kilograms in the customs data. For the pairs for which we can identify a common quantity unit, we compute the foreign cost share as the ratio of the customs unit value and the scanner unit value. This procedure is arguably imperfect, since we cannot be sure that we compare the same barcodes in the customs and scanner data. However, we believe that it carries some information on the magnitude of the foreign cost share.[24] Doing that, we find an average foreign cost share of only 28%, which is at the bottom end of the range identified in Berger et al. (2012).

In initial work, we have matched the unit values, along with the unit of measure used in both customs and scanner data, for approximately two thousand category-country pairs.

[23] See Sangani (2025) for a similar argument in the context of commodity price shocks.

[24] Within the roughly two thousand country-category pairs we merge between datasets, 95% of all recovered estimates of the foreign cost share are less than one, which should be true by definition.

Within these matched category-country pairs, we recover a mean estimate of the foreign cost share of 0.25 and a median estimate of 0.28. Reassuringly, 95% of all recovered estimates are less than one, which should be true by definition. These estimates are ultimately lower than what previous research has documented, with Berger et al. (2012) recovering a range of foreign cost shares between 30%-50% using U.S. BLS micro-data. Berger et al. (2012) also document considerably heterogeneity by category and origin country, which we have yet to explore in our country.

This component of the paper remains a work-in-progress. Still, our headline estimate of tariff pass-through into retail unit values of 33%, when combined with existing estimates of border pass-through of 100% (Amiti et al. 2019; Fajgelbaum et al. 2020; Cavallo et al. 2021), suggests that domestic consumers bore a third of the incidence of U.S. import tariffs on China, whereas domestic retailers absorbed two thirds of this incidence. However when we consider that our estimate of 33% is indistinguishable statistically from the 28% mean foreign cost share we recover, it becomes clear that we cannot reject the possibility import tariffs were borne entirely by U.S. consumers, with retailers absorbing very little, if any, of this cost shock. Still, this section remains a work-in-progress as we refine and validate our estimates of the foreign cost share.

6 Conclusion

This paper is the first to document positive pass-through into U.S. consumer prices associated with tariffs levied by the U.S. on Chinese exports during the trade war of 2018-2019. In particular, we attempt to bridge the existing gap between estimates of complete pass-through at the border and the lack of evidence at U.S. stores of any tariff pass-through. In doing so, we highlight the difference between within-product pass-through, which we document at 15%, and pass-through into average unit values, which we document was at least 33%. Our data allows us to explicitly show that this discrepancy is due to a reshuffling of products towards smaller sizes, such that sticker prices remain the same despite tariffs being passed through to consumers via an increase in average price per unit weight. Estimates of tariff pass-through which take individual products as the relevant unit of measure are biased downwards to the "product replacement bias" described in Nakamura and Steinsson (2011).

In ongoing work, we consider the foreign cost share of retail goods sold in the U.S. By comparing unit values in customs data to those found in scanner data, we seek to understand how full pass-through "ought" to manifest in U.S. retail prices, and in doing so place bounds on the share of costs borne by U.S. consumers and costs borne by U.S. retailers. Our current work, while early, suggests that tariff pass-through into U.S. consumer prices as complete,

once the two sources of bias discussed here are addressed.

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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: Anti-Competitive Effects of Tariffs on non-Targeted Products

	(1) log Price	(2) log Price	(3) log Quantity	(4) log Quantity	(5) log Stores	(6) log Stores
$\log(1+\tau_CN)$	0.009	0.022	-0.164	-0.159	-0.048	-0.103
	(0.015)	(0.018)	(0.117)	(0.122)	(0.067)	(0.064)
$\log(1+\tau_CN) \times (CNshare > 0)$		-0.023		-0.008		0.102**
		(0.019)		(0.090)		(0.046)
α_{ir}, α_{rt}, α_{jt}	✓	✓	✓	✓	✓	✓
α_{gt}	✓	✓	✓	✓	✓	✓
R^2	1.00	1.00	0.97	0.97	0.96	0.96
Observations	23044313	23044313	23044313	23044313	23044313	23044313

*Notes: This table provides estimates of β from applying OLS to Equation 3. From left to right, columns define y_{irt} as, respectively, barcode-retailer price, units sold at barcode-retailer-month level, and the number of stores exhibiting non-zero sales of barcode i within retail chain r and month t. Chinese varieties are removed from the sample, and category-time fixed effects are replaced by department-time fixed effects. The second row interacts China tariffs with an indicator for whether a given retailer-category combination exhibits any expenditure on Chinese exports. Standard errors are clustered two-way at the category-country and month level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Back to Section 3.3.*

Table A.2: Estimates of Tariff Pass-through and Substitution (unbalanced panel)

	(1) log Price	(2) log Price	(3) log Quantity	(4) log Quantity
$\log(1+\tau)$	0.141***	-0.005	-0.171	-0.590**
	(0.032)	(0.042)	(0.143)	(0.224)
Sample	Balanced	Unbalanced	Balanced	Unbalanced
Fixed Effects (α_{irt})	✓	✓	✓	✓
R^2	1	1	1	1
N	23290527	60378252	23290527	60378252

*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. The balanced sample consists of barcodes present throughout the entire sample period, while the unbalanced panel consists of all barcode-retailer observations. Standard errors are clustered two-way at the category-country and month level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Back to Section 3.3.*

Table A.3: Tariff Effects on Barcode-Retailer Net Entry

	(1) E_{irt}	(2) E_{irt}	(3) E_{irt}	(4) Survive	(5) Survive	(6) Survive
$\log(1+\tau)$	-0.165*			-0.109		
	(0.083)			(0.079)		
$\log(1+\tau) \times$ Wave 3		-0.157*	-0.131		-0.108	-0.127
		(0.079)	(0.090)		(0.075)	(0.078)
$\log(1+\tau) \times$ Wave 4		-0.007			-0.100	
		(0.071)			(0.087)	
Wave 3			Wave 3			Wave 3
Sample			<=2019			<=2019
R^2	0.65	0.65	0.67	0.73	0.73	0.77
Observations	110671896	110671896	44838117	110671896	110671896	44838117

*Notes: Columns (1)-(3) define y_{irt} as a dummy for whether barcode i exhibits non-zero sales at stores of retailer r in period t. Columns (4)-(6) define y_{irt} as a dummy for whether t is between the first and last period exhibiting non-zero sales of i at chain r. The interactions depict an interaction between tariff changes and an indicator for that tariff change being associated with wave 3 or wave 4a. Standard errors are clustered two-way at the category-country and month level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Back to Section 3.3.*

Table A.4: Tariff Effects on Barcode Net Entry

	(1) E_{it}	(2) E_{it}	(3) E_{it}	(4) Survive	(5) Survive	(6) Survive
$\log(1+\tau)$	-0.249**			-0.471***		
	(0.096)			(0.113)		
$\log(1+\tau) \times$ Wave 3		-0.238**	-0.253*		-0.454***	-0.465***
		(0.094)	(0.125)		(0.112)	(0.156)
$\log(1+\tau) \times$ Wave 4		-0.078			-0.205	
		(0.103)			(0.166)	
Wave 3			Wave 3			Wave 3
Sample			<=2019			<=2019
R^2	0.63	0.63	0.63	0.65	0.65	0.66
Observations	9,166,079	9,166,079	3,892,074	9,166,079	9,166,079	3,892,074

*Notes: Columns (1)-(3) define y_{irt} as a dummy for whether barcode i exhibits non-zero sales in period t. Columns (4)-(6) define y_{it} as a dummy for whether t is between the first and last period exhibiting non-zero sales of i. The interactions depict an interaction between tariff changes and an indicator for that tariff change being associated with wave 3 or wave 4a. Standard errors are clustered two-way at the category-country and month level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Back to Section 3.3.*

Table A.5: Category-Level Pass-through and Compositional Effects (Constant Units within Category)

	(1) Log Price	(2) Log Price	(3) Log Quantity	(4) Log Quantity	(5) Log Price	(6) Log Price	(7) Log Weight	(8) Log Weight
$\log(1+\tau)$	0.093*	0.539***	-0.138	-0.450	0.051	-0.016	-0.042	-0.555***
	(0.053)	(0.156)	(0.190)	(0.408)	(0.038)	(0.093)	(0.044)	(0.187)
Balanced	✓		✓		✓		✓	
Unbalanced		✓		✓		✓		✓
Price per weight	✓	✓						
Raw sticker price					✓	✓		
R^2	1	1	1	1	1	1	1	1
Observations	2,544,861	2,544,861	2,544,861	2,544,861	2,544,861	2,544,861	2,544,861	2,544,861

*Notes: This table provides estimates of β from applying OLS to Equation 4. All models include fixed effects by country-category-retailer, retailer-month, category-month, and country-month. From left to right, dependent variables are: average price per unit weight, total quantity sold (in units of weight), average sticker price (not per unit weight), and the average weight of barcodes sold. All averages are calculated using quantity sales weights. Columns (1), (3), (5), and (7) construct variables using the balanced panel of continuing barcodes, while Columns (2), (4), (6), and (8) use the raw unbalanced panel to construct averages. For each retailer-category pair, we calculate the unit of measure in 2017 with the greatest expenditure, and only include barcodes throughout the sample which are measured in this same unit, such that all within retail-category comparisons over time are within the same units. Standard errors are clustered two-way at the category-country and month level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.*

Table A.6: Category-Level Pass-through and Compositional Effects (Constant Units within Category and no “Count" Units)

	(1) Log Price	(2) Log Price	(3) Log Quantity	(4) Log Quantity	(5) Log Price	(6) Log Price	(7) Log Weight	(8) Log Weight
$\log(1+\tau)$	0.059	0.400	-0.656	-0.670	-0.049	-0.128	-0.109	-0.528**
	(0.104)	(0.268)	(0.439)	(0.427)	(0.062)	(0.172)	(0.090)	(0.252)
Balanced	✓		✓		✓		✓	
Unbalanced		✓		✓		✓		✓
Price per weight	✓	✓						
Raw sticker price					✓	✓		
R^2	1	1	1	1	1	1	1	1
Observations	2,116,290	2,116,290	2,116,290	2,116,290	2,116,290	2,116,290	2,116,290	2,116,290

*Notes: This table provides estimates of β from applying OLS to Equation 4. All models include fixed effects by country-category-retailer, retailer-month, category-month, and country-month. From left to right, dependent variables are: average price per unit weight, total quantity sold (in units of weight), average sticker price (not per unit weight), and the average weight of barcodes sold. All averages are calculated using quantity sales weights. Columns (1), (3), (5), and (7) construct variables using the balanced panel of continuing barcodes, while Columns (2), (4), (6), and (8) use the raw unbalanced panel to construct averages. For each retailer-category pair, we calculate the unit of measure in 2017 with the greatest expenditure, and only include barcodes throughout the sample which are measured in this same unit, such that all within retail-category comparisons over time are within the same units. We further exclude all retail-category pairs for which "counts" are the dominant unit of measure. Standard errors are clustered two-way at the category-country and month level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.*

Table A.7: Firm-Category-Level Pass-through and Compositional Effects

	(1) Log Price	(2) Log Price	(3) Log Quantity	(4) Log Quantity	(5) Log Price	(6) Log Price	(7) Log Weight	(8) Log Weight
$\log(1+\tau)$	0.121***	0.414**	-0.234	-0.679**	0.096***	0.108	-0.026	-0.306
	(0.035)	(0.199)	(0.174)	(0.300)	(0.034)	(0.066)	(0.030)	(0.218)
Balanced	✓		✓		✓		✓	
Unbalanced		✓		✓		✓		✓
Price per weight	✓	✓						
Raw sticker price					✓	✓		
R^2	1	1	1	1	1	1	1	1
Observations	6,816,448	6,816,448	6,816,448	6,816,448	6,816,448	6,816,448	6,816,448	6,816,448

*Notes: This table provides estimates of β from applying OLS to a variation of Equation 4. In this case data are aggregated to the firm-category-country-retailer level, which is a finer resolution when compared to category-country-retailer. All models include fixed effects by firm-country-category-retailer, retailer-month, category-month, and country-month. From left to right, dependent variables are: average price per unit weight, total quantity sold (in units of weight), average sticker price (not per unit weight), and the average weight of barcodes sold. All averages are calculated using quantity sales weights. Columns (1), (3), (5), and (7) construct variables using the balanced panel of continuing barcodes, while Columns (2), (4), (6), and (8) use the raw unbalanced panel to construct averages. Standard errors are clustered two-way at the category-country and month level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.*

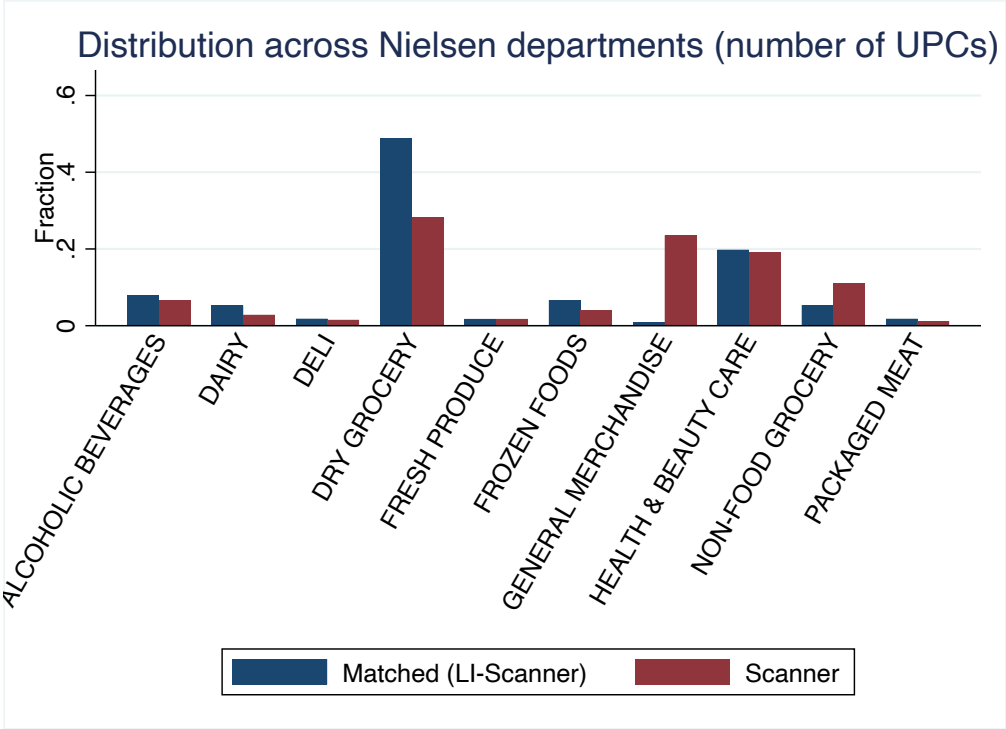
Table A.8: Firm-Category-Level Pass-through and Compositional Effects (Constant Units within Firm-Category-Retailer)

	(1) Log Price	(2) Log Price	(3) Log Quantity	(4) Log Quantity	(5) Log Price	(6) Log Price	(7) Log Weight	(8) Log Weight
$\log(1+\tau)$	0.124***	0.420**	-0.236	-0.646**	0.103***	0.122*	-0.021	-0.298
	(0.035)	(0.202)	(0.175)	(0.302)	(0.034)	(0.066)	(0.031)	(0.222)
Balanced	✓		✓		✓		✓	
Unbalanced		✓		✓		✓		✓
Price per weight	✓	✓						
Raw sticker price					✓	✓		
R^2	1	1	1	1	1	1	1	1
Observations	6,758,384	6,758,384	6,758,384	6,758,384	6,758,384	6,758,384	6,758,384	6,758,384

*Notes: This table provides estimates of β from applying OLS to a variation of Equation 4. In this case data are aggregated to the firm-category-country-retailer level, which is a finer resolution when compared to category-country-retailer. All models include fixed effects by firm-country-category-retailer, retailer-month, category-month, and country-month. From left to right, dependent variables are: average price per unit weight, total quantity sold (in units of weight), average sticker price (not per unit weight), and the average weight of barcodes sold. All averages are calculated using quantity sales weights. Columns (1), (3), (5), and (7) construct variables using the balanced panel of continuing barcodes, while Columns (2), (4), (6), and (8) use the raw unbalanced panel to construct averages. For each firm-retailer-category pair, we calculate the unit of measure in 2017 with the greatest expenditure, and only include barcodes throughout the sample which are measured in this same unit, such that all within retail-category comparisons over time are within the same units. Standard errors are clustered two-way at the category-country and month level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.*

A.2 Additional Figures

Figure A.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). Back to Section 2.

Figure A.2: Trade War Tariffs by Dataset

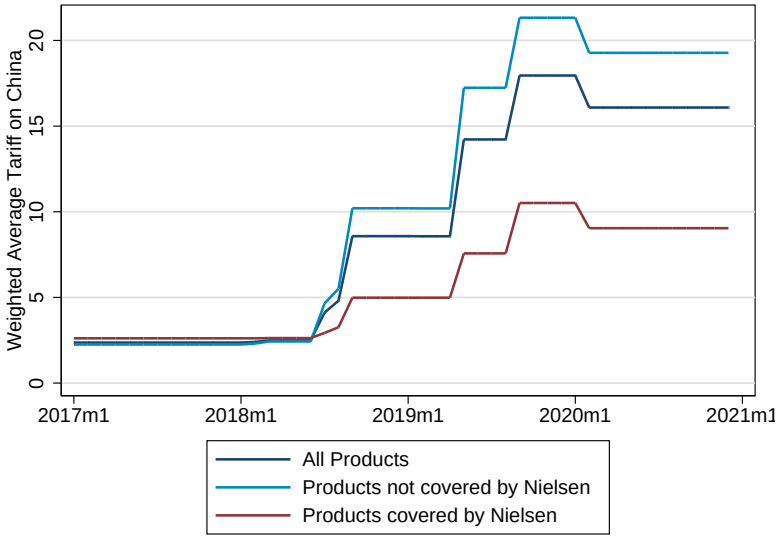
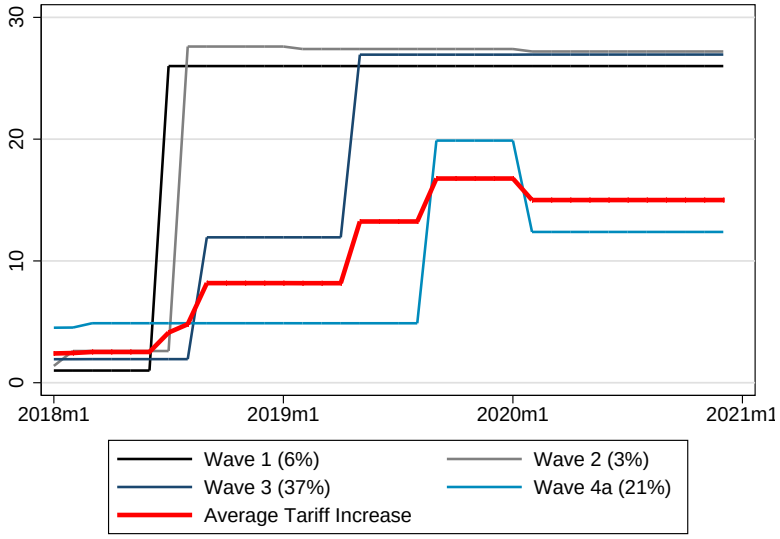
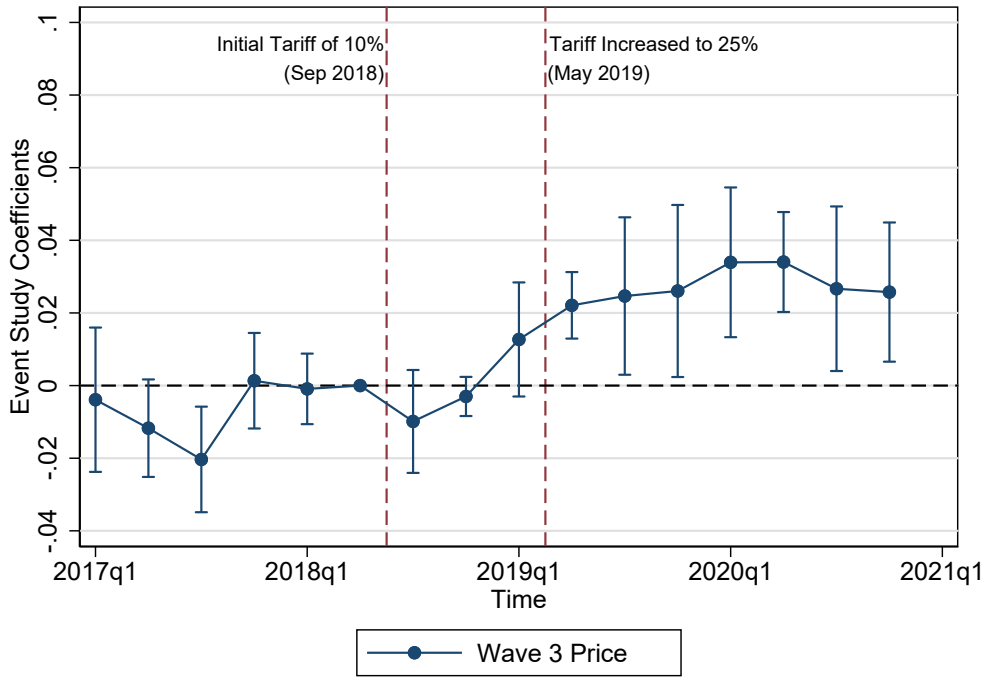


Figure A.3: Trade War Tariffs by Wave within NielsenIQ Sample



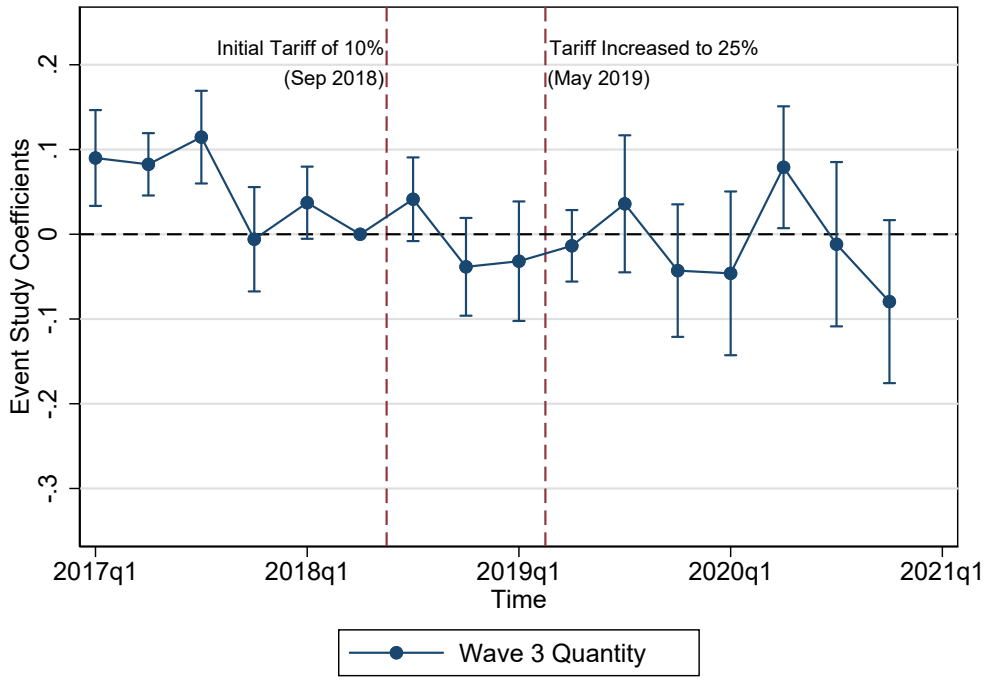
Notes: Figure 2 provides the average tariff rate applied by the U.S. to imports from China over time, decomposed into categories covered by the NielsenIQ data and all other categories. Figure 3 provides the average tariff increase over time within NielsenIQ categories, and denotes the total share of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

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



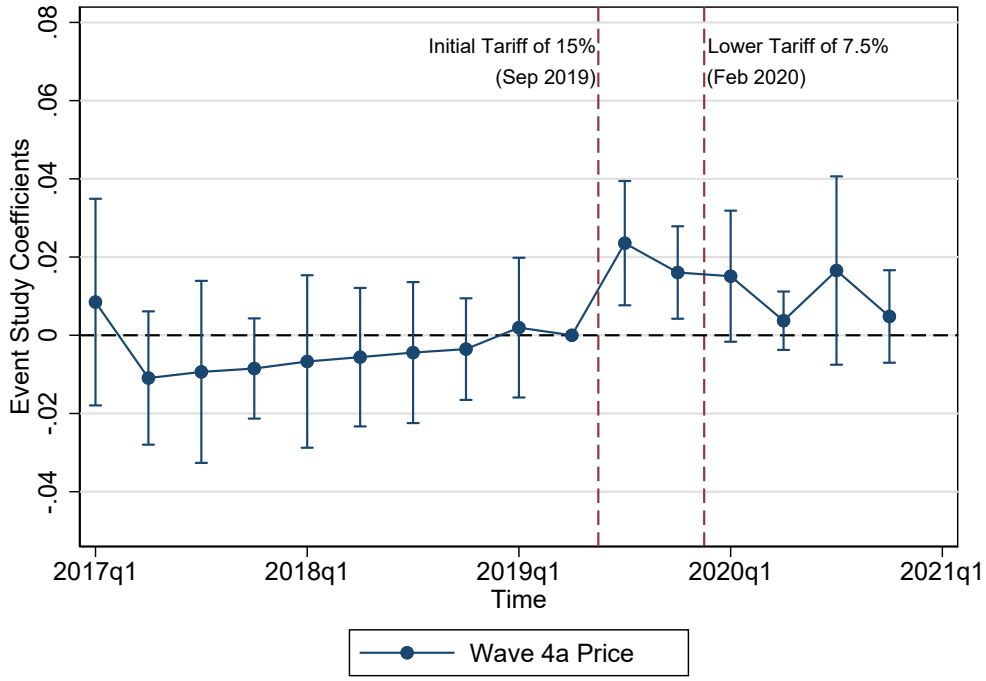
Notes: This figure provides estimates associated with estimating Equation 2. The dependent variable is p_{irt}: prices at the barcode-retailer-month level. All never-tariff categories are included as the control group, whereas the only treated group included are those categories targeted by tariff wave 3. Barcode-retailer, retailer-month, category-month, and country-month fixed effects included. 95% confidence intervals included, with standard errors clustered two-way at the category-country and month level. Back to Section 3.2.

Figure A.5: Event Study Estimates: Wave 3 Quantity



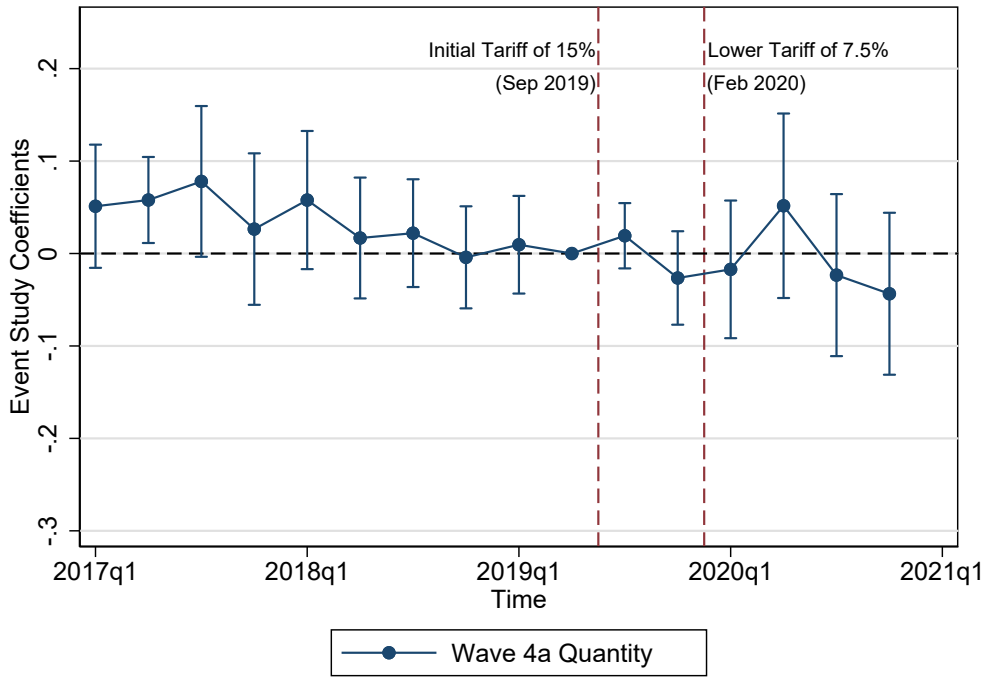
Notes: This figure provides estimates associated with estimating Equation 2. The dependent variable is q_{irt}: quantity sold at the barcode-retailer-month level. All never-tariff categories are included as the control group, whereas the only treated group included are those categories targeted by tariff wave 3. Barcode-retailer, retailer-month, category-month, and country-month fixed effects included. 95% confidence intervals included, with standard errors clustered two-way at the category-country and month level. Back to Section 3.2.

Figure A.6: Event Study Estimates: Wave 4a Prices



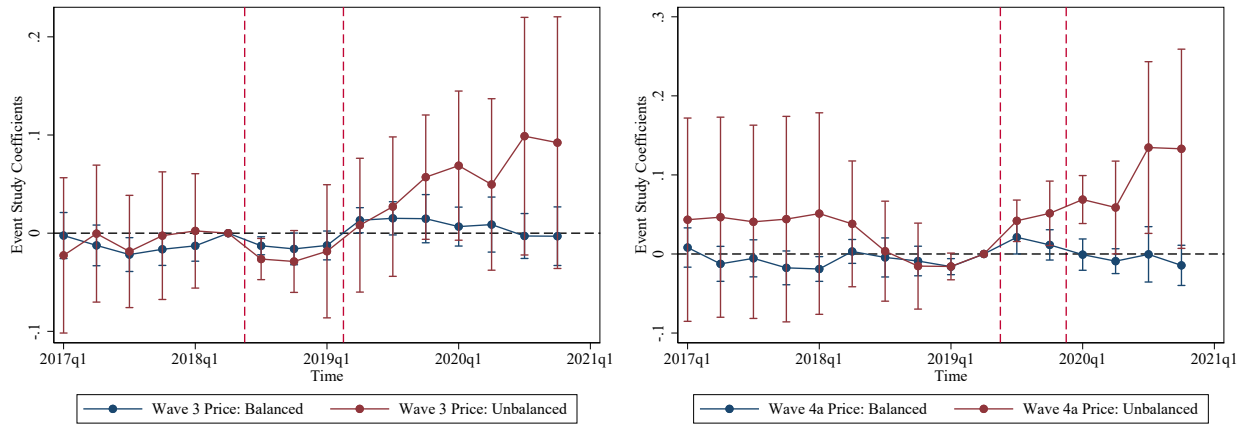
Notes: This figure provides estimates associated with estimating Equation 2. The dependent variable is p_{irt}: prices at the barcode-retailer-month level. All never-tariff categories are included as the control group, whereas the only treated group included are those categories targeted by tariff wave 4a. Barcode-retailer, retailer-month, category-month, and country-month fixed effects included. 95% confidence intervals included, with standard errors clustered two-way at the category-country and month level. Back to Section 3.2.

Figure A.7: Event Study Estimates: Wave 4a Quantity



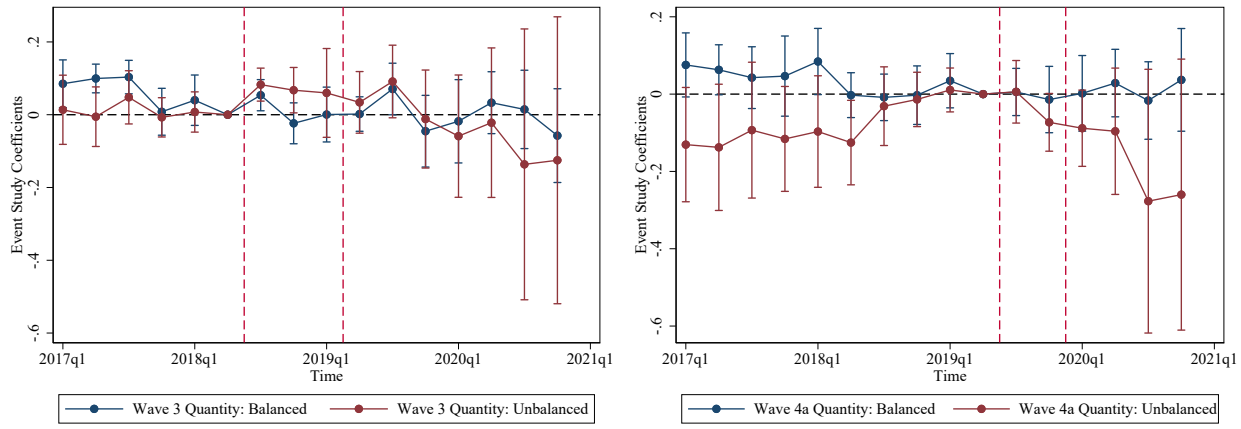
Notes: This figure provides estimates associated with estimating Equation 2. The dependent variable is q_{irt}: quantity sold at the barcode-retailer-month level. All never-tariff categories are included as the control group, whereas the only treated group included are those categories targeted by tariff wave 4a. Barcode-retailer, retailer-month, category-month, and country-month fixed effects included. 95% confidence intervals included, with standard errors clustered two-way at the category-country and month level. Back to Section 3.2.

Figure A.8: Event Study Estimates for Category Average Price Pass-through



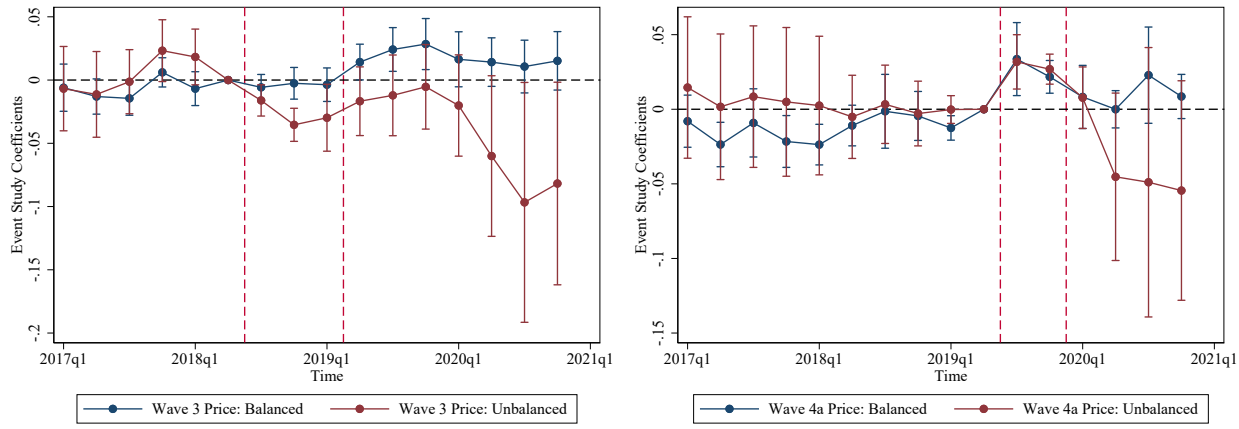
Notes: This figure provides estimates associated with an event study design at the aggregated country-category-retailer level. All models include fixed effects by country-category-retailer, retailer-month, category-month, and country-month. The dependent variable is $\bar{p}_{jcrt}$: the quantity-weighted average price per unit weight. Left panel: all never-tariff categories are included as the control group, whereas the only treated group included are those categories targeted by tariff wave 3. Right Panel: never-tariff categories are control but only tariff wave 4a categories are treated. Vertical lines denote tariff changes. The red series uses the unbalanced panel to calculate average prices, the blue series uses the balanced panel to calculate average prices. 95% confidence intervals included, with standard errors clustered two-way at the category-country and month level. Return to Section 4.2.

Figure A.9: Event Study Estimates for Category Quantity Effects



Notes: This figure provides estimates associated with an event study design at the aggregated country-category-retailer level. All models include fixed effects by country-category-retailer, retailer-month, category-month, and country-month. The dependent variable is q_{jcrt}: total quantity (in unit weight) sold. Left panel: all never-tariff categories are included as the control group, whereas the only treated group included are those categories targeted by tariff wave 3. Right Panel: never-tariff categories are control but only tariff wave 4a categories are treated. Vertical lines denote tariff changes. The red series uses the unbalanced panel to calculate average prices, the blue series uses the balanced panel to calculate average prices. 95% confidence intervals included, with standard errors clustered two-way at the category-country and month level. Return to Section 4.2.

Figure A.10: Event Study Estimates for Category Average Sticker Price Pass-through



Notes: This figure provides estimates associated with an event study design at the aggregated country-category-retailer level. All models include fixed effects by country-category-retailer, retailer-month, category-month, and country-month. The dependent variable is $\bar{p}^{raw}_{jcrt}$*: the quantity-weighted raw average price of barcodes sold, with no normalization by weight. Left panel: all never-tariff categories are included as the control group, whereas the only treated group included are those categories targeted by tariff wave 3. Right Panel: never-tariff categories are control but only tariff wave 4a categories are treated. Vertical lines denote tariff changes. The red series uses the unbalanced panel to calculate average prices, the blue series uses the balanced panel to calculate average prices. 95% confidence intervals included, with standard errors clustered two-way at the category-country and month level. Return to Section 4.2.*

B Additional Empirical Results and Derivations

B.1 Comparison to Cavallo et al. (2021)

This section provides an overview of our comparison to the estimating equation in Cavallo et al. (2021). First, recall our main estimating equation, which is a triple-difference at the barcode level:

$$\ln(p_{irt}) = \beta \ln(1 + \tau_{jct}) + \gamma_{i,q(t)} + \alpha_{ir} + \alpha_{rt} + \alpha_{c(i),t} + \alpha_{j(i),t} + \epsilon_{irt}$$

This is simply a re-stating of Equation 1. In this case we estimate the effect of level changes in tariffs on level changes in prices while controlling for barcode-retailer pair level prices differentials, retailer-period shocks, category-period shocks, and country-period shocks. Thus, we interpret our estimates as a triple-difference.

Cavallo et al. (2021) take a slightly different approach, although the unit of observation remains a product-retailer combination. Mapping their estimating equation into our notation, we derive the following estimating equation:[25]

$$\begin{aligned}\Delta \ln p_{irt} = \alpha_{c(i)} + \phi^{w}_{CN} + \sum_{\ell=0}^{11} \beta^{\tau}_{\ell} \Delta \ln \tau_{c(i)j(i),t-\ell} \\ + \sum_{\ell=0}^{11} \beta^{ex}_{\ell} \Delta \ln EX_{j(i),t-\ell} + \sum_{\ell=0}^{11} \beta^{ppi}_{\ell} \Delta \ln PPI_{j(i),t-\ell} + \epsilon_{irt}\end{aligned}$$

where the Δ operator denotes a first-difference over time periods, which are at the month level. $\alpha_{c(i)}$ denotes category-specific trends in price, while ϕ^{w}_{CN} denote trends that are specific to Chinese barcodes and specific to each wave. In our implementation, this is equivalent to having three additional trends: Chinese varieties in non-tariff categories, Chinese varieties in wave 3 categories, and Chinese varieties in wave 4a categories.

τ_{cjt} is the tariff rate, as in our main estimating equation, such that $\sum_{\ell=0}^{11} \hat{\beta}^{\tau}_{\ell}$ denotes tariff pass-through one year after tariff implementation. Cavallo et al. (2021) then also control for the exchange rate of country $j(i)$ and the producer price index in country $j(i)$. Although the exchange rate and producer price index terms are included in their headline estimates of tariff pass-through into border prices, Cavallo et al. (2021) do not include these controls in their retail specification, such that there are no origin-specific controls other than the trend terms ϕ_{CN}.

[25] Note that product categories in our setting are explicitly HS8 categories, whereas those used in Cavallo et al. (2021) are defined by the BLS as "primary stratum lower", which is somewhere between HS4 and HS6, in terms of disaggregation.

Since our analysis is at the barcode-retailer level, we augment Cavallo et al. (2021) to include a trend that is retail-chain specific as well, α_r. The most direct comparison then is between our triple-difference headline estimating equation and the following estimating equation associated with Cavallo et al. (2021):

$$\Delta \ln p_{irt} = \alpha_{c(i)} + \alpha_r + \phi^w_{CN} + \sum_{\ell=0}^{11} \beta^\tau_\ell \Delta \ln \tau_{c(i)j(i)t} + \epsilon_{irt}$$

Table B.1 provides this comparison. Columns (1)-(3) provides estimates associated with the first-difference approach in Cavallo et al. (2021). Column (1) includes exchange rates and producer price indices (with all lagged values up to a year) as controls, whereas column (2) provides the most direct comparison with Cavallo et al. (2021) by excluding those controls. Column (3) makes use of the same set of fixed effects as our baseline analysis (category-time, country-time, and retailer-time) but within the first-difference structure of Cavallo et al. (2021).[26]

Interestingly, we find positive pass-through into retail prices associated with the contemporaneous change in tariff rates $\Delta \ln \tau_t$, with estimates that are positive for all three model variations and in line with the estimates recovered in our baseline analysis. When we sum the lagged effects of tariffs over a year, however, we recover highly imprecise estimates which fluctuate between -0.127 and 0.236, depending on specification.

The fact that tariffs have an immediate effect on prices is highlighted in our event study estimates, and suggests that even with the first-difference structure used by Cavallo et al. (2021), within our data there is still a clear effect of tariffs on retail prices.

Columns (4)-(6) of Table A.1 take our baseline specification and remove the country-year fixed effects, instead opting for the inclusion of controls (exchange rates, producer price indices) in column (5) and the exclusion of all country-period controls in column (6). While all estimates remain positive, the relaxing of country-period fixed effects surprisingly reduces the estimated tariff pass-through. Of course it is possible that in this case the exchange rate and producer price indices are “bad controls" as they are endogenously determined by changes in tariffs as well.

In summary, we still find tariff pass-through of similar magnitude when we implement the first-difference estimator associated with Cavallo et al. (2021), although we find similarly null effects when we aggregate all lagged effects. This may be due to the staggered roll-out of tariffs over time, such that lagged tariff changes are sometimes at odds, in terms of the level change they represent, with the contemporaneous changes in tariff rates.

[26] Thus, the barcode-retailer fixed effects are differenced out.

Table B.1: Comparison to Cavallo et al. (2021)

	(1) Δ lnPrice	(2) Δ lnPrice	(3) Δ lnPrice	(4) log Price	(5) log Price	(6) log Price
$\Delta \ln \tau_t$	0.113***	0.079*	0.230*			
	(0.037)	(0.046)	(0.118)			
$\Delta \ln \tau_{t-1}$	0.016	0.034	0.012			
	(0.085)	(0.090)	(0.122)			
$\Delta \ln \tau_{t-2}$	0.047	0.081*	0.288***			
	(0.031)	(0.044)	(0.099)			
$\Delta \ln \tau_{t-3}$	-0.050	-0.008	-0.022			
	(0.066)	(0.071)	(0.143)			
$\Delta \ln \tau_{t-4}$	0.081	0.067	0.208***			
	(0.054)	(0.042)	(0.070)			
$\Delta \ln \tau_{t-5}$	0.081	0.084	0.088			
	(0.062)	(0.062)	(0.070)			
$\Delta \ln \tau_{t-6}$	-0.096	-0.104	0.026			
	(0.068)	(0.069)	(0.040)			
$\Delta \ln \tau_{t-7}$	0.038	0.034	-0.034			
	(0.070)	(0.078)	(0.098)			
$\Delta \ln \tau_{t-8}$	-0.087	-0.029	-0.348**			
	(0.062)	(0.075)	(0.141)			
$\Delta \ln \tau_{t-9}$	-0.077	-0.131	0.049			
	(0.093)	(0.101)	(0.169)			
$\Delta \ln \tau_{t-10}$	-0.169	-0.192	-0.267***			
	(0.143)	(0.148)	(0.045)			
$\Delta \ln \tau_{t-11}$	-0.014	-0.043	0.006			
	(0.107)	(0.117)	(0.196)			
$\log(1+\tau)$				0.158***	0.100***	0.068***
				(0.036)	(0.026)	(0.021)
Estimate ($\sum \hat{\beta}^{\tau}$)	-0.116	-0.127	0.236			
SE	(0.273)	(0.291)	(0.411)			
Exchange Rate	✓				✓	
PPI	✓				✓	
Fixed Effects	m+r+phi	m+r+phi	mt+jt+rt	ir+mt+jt+rt	ir+mt+rt	ir+mt+rt
Sample	<=2019	<=2019	<=2019	<=2019	<=2019	<=2019
Wave	Wave 3	Wave 3	Wave 3	Wave 3	Wave 3	Wave 3
R^2	0.000	0.001	0.040	0.998	0.998	0.998
N	6,674,016	6,674,016	6,673,800	10010700	10010844	10010844

*Notes: This table provides estimates of β from applying OLS to Equation 3. From left to right, columns define y_{irt} as, respectively, barcode-retailer price, units sold at barcode-retailer-month level, and the number of stores exhibiting non-zero sales of barcode i within retail chain r and month t. Chinese varieties are removed from the sample, and category-time fixed effects are replaced by department-time fixed effects. The second row interacts China tariffs with an indicator for whether a given retailer-category combination exhibits any expenditure on Chinese exports. Standard errors are clustered two-way at the category-country and month level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Back to Section 3.3.*