A Environment

In this section we present a simple static framework to motivate our regression specifications. Consider a supply chain with the following sequence. A firm located in country $j$ exports good $i$ at time $t$ to a US importer at a US dollar price $P_{i,j,t}^I$. The importer then pays an ad-valorem tariff $\tau_{i,j,t}$ to the government, resulting in a total import cost of $P_{i,j,t}^I (1 + \tau_{i,j,t})$. Finally, the importer combines this input with proportional marketing and distribution costs before selling that good to consumers at a retail price $P_{i,j,t}^R$ (also in dollars).

We assume the foreign exporter manufactures the good using a Cobb-Douglas technology with constant returns to scale that uses some inputs (like labor) whose prices are sticky in the local currency and others (like imported inputs) whose prices are not. We therefore write the exporter’s marginal cost, translated to US dollars, as

$$C_{i,j,t}^I = A_{i,j,t} (W_{j,t} S_j t) \phi,$$

where $A_{i,j,t}$ captures the combined effect of the firm’s productivity and the cost of inputs with prices sticky in the foreign currency, $W_{j,t}$ represents the price of the sticky local currency input (such as the wage), $S_{j,t}$ is the number of US dollars purchased by each unit of country $j$’s currency, and $\phi$ is the output elasticity of the exporter’s production function with respect to that local currency input.

The exporter’s price equals a markup over this marginal cost: $P_{i,j,t}^I = \mu_{i,j,t} C_{i,j,t}^I$. The exporter incurs a cost when it changes its price for the good, so will only do so when the resulting increase in operating profits exceeds this cost. When the exporter changes the price, its markup $\mu_{i,j,t}$ is assumed to be a function of its market share, which we assume depends on its own price relative to an industry price level $P_t^I$, multiplied by the tariff, since import demand for the good depends on its price inclusive of tariffs. We therefore write:

$$\mu_{i,j,t}^I = \mu^I \left((1 + \tau_{i,j,t}) P_{i,j,t}^I / P_t^I ; \theta^I\right),$$

where
\( \theta^I \) collects parameters governing the shape of import demand and use \( \Gamma^I \equiv -\frac{\partial \ln \mu^I(x)}{\partial \ln x} \) to denote the opposite of the elasticity of the markup.\(^1\) We take logs, differentiate, and substitute these relationship to write:

\[
d\ln (P_{i,j,t}^I) = \gamma^I d\ln (1 + \tau_{i,j,t}) - \gamma^I d\ln (P_t^I) + \beta^I d\ln (W_{j,t}) + \beta^I d\ln (S_{j,t}), \tag{A1}
\]

where \( \gamma^I \equiv -\frac{\Gamma^I}{1+\Gamma^I} \) is the passthrough of tariffs to the ex-tariff import price and \( \beta^I \equiv \frac{\phi}{1+\Gamma^I} \) is the passthrough of local costs and exchange rates to the import price. Since \( \gamma^I \) equals tariff passthrough to ex-tariff import prices, \( 1+\gamma^I \) equals the rate of passthrough from tariffs to total (i.e. inclusive of tariff) import prices.

Equation (A1) forms the basis for our empirical strategy. Because some exporters may choose not to change prices, some of our estimates using trade data are conditional on observing a price change. In the extreme case with \( \gamma^I = -1 \), it would imply that ex-tariff import prices fell proportionately with tariffs and the total price of imports remained constant. This hypothetical would reveal that the passthrough of tariffs to the total import cost was zero (i.e. \( 1+\gamma^I = 0 \)) and that the tariff’s cost fell entirely on the exporter. Alternatively, if \( \gamma^I \) were estimated to equal 0, it would imply that ex-tariff import prices did not change with the tariffs, but rather, that the tariffs were fully passed through to the total import price (i.e. \( 1+\gamma^I = 1 \)). The importer, in this case, bears much of the tariff’s cost. We estimate a closely related specification in our analysis of passthrough to retail prices.

B More Import and Export Results

B.1 More Details on Import Price Data

In the paper we mention that we focus only on market transactions in the BLS import data. More than one-third of the BLS import prices are non-market transactions such as intrafirm trade or shipments among related parties. Neiman (2010) studies the differences in these market and related party prices. In our analyses of the tariff on Chinese imports, we also exclude a small number of goods that are impacted both by a China tariff and another product-based tariff (such as steel and aluminum products, lumber, washing machines, and solar panels). We additionally exclude data on imports from India because in June 2019 the United States ended

\(^1\)We assume the exporter is too small to internalize any impact on the final retail price charged by the importer.
India’s developing country exemption, which had given it access to US most favored nation tariff rates.

**B.2 Frequency and Size of Imports**

The price indices in Figure 1(a) reflect the frequency of import price changes as well as the size of any non-zero price changes. Since the BLS data are at the level of individual goods, we can observe if the stability of ex-tariff prices reflects “wait and see” behavior or any other important changes in the patterns of price stickiness.

![Figure A1: Frequency of Monthly Price Changes (Quarterly Averages)](image)

Figure 1(a) plots the share of prices each month which decrease, averaged across the three months in each quarter to smooth the otherwise volatile series. It does this separately for four categories of goods: those of the type unaffected by the tariffs and imported from countries other than China, those unaffected even though they are imported from China, those affected but imported from outside of China, and those affected and imported from China, where only this latter group includes goods where the importer must actually pay a tariff. There are no obvious differences across the four groups and, if anything, the prices of products in that last set of goods appear to be the most stable. Figure 1(b) plots the equivalent statistics for price increases and, again, finds little evidence of important changes in pricing behavior brought about by the tariffs.
B.3 Additional Regression Results for Import Prices

Table A1 reports some additional results from estimating Equation (1) in the paper using monthly data from January 2005 to August 2019. Column (1) reports the cumulative impact of 12 months of tariffs in a specification that does not condition on any other variables. The estimated coefficient of -0.079 means, for example, that a 10 percent tariff would be associated with a 0.8 percent lower ex-tariff price and a 9.2 percent higher overall price faced by the importer. Column (2), reported also in the paper, adds sectoral fixed effects plus the China-specific fixed effects $\phi$ and the magnitude of this estimate is roughly preserved. Column (3) removes the tariff and China-specific covariates and estimates a relatively standard passthrough regression, showing that when the dollar depreciates by about 10 percent, import prices rise by about 2.19 percent. Finally, in Column (4) we estimate the tariff impact using a specification that also controls for sectoral effects and exchange rates. Our exchange rate passthrough estimate is largely unchanged but the tariff response drops to a value that is statistically indistinguishable from zero.

We now consider a second type of regression in which we only include non-zero price changes. In particular, for each price spell of good $i$, we define $t_1$ as the first month of the spell and $t_0$ as the first month of the previous spell. We then estimate:

$$\frac{1}{t_1 - t_0} \ln \left( \frac{P_{i,j,k,t_1}}{P_{i,j,k,t_0}} \right) = \delta_k + \phi_{CN} + \phi_{-CN} + \gamma \tau_{CN,k,t_1} + \beta_{S} \frac{1}{t_1 - t_0} \ln \left( \frac{S_{j,t_1}}{S_{j,t_0}} \right) + \beta_{X} \frac{1}{t_1 - t_0} \ln \left( \frac{X_{j,t_1}}{X_{j,t_0}} \right) + \epsilon_{i,j,k,t_1,t_0}, \quad (A2)$$

where the term $(t_1 - t_0)$ serves to scale the changes so all correspond to a monthly frequency. In this specification, $\tau_{CN,k,t_1}$ equals the tariff level for goods from China in sector $k$ at $t_1$ and is meant to allow estimates of $\gamma$ to capture differential inflation rates for goods impacted by the tariffs.$^2$ Since the changes in the price, exchange rate, and producer price index are all scaled to represent monthly changes, we report the estimate of $\gamma$ multiplied by 12 to capture the annualized equivalent of the change in inflation associated with goods affected by the tariffs. Given this, plus the fact that these regressions drop any observations where the left-hand-side equals zero, these estimates would be expected to be larger in magnitude than what was found

---

$^2$This specification may not be well-suited for thinking about changes where $t_0$ is after the tariff was imposed, but our results appear qualitatively robust to dropping such observations.
### Table A1: Regression Analysis of Chinese Import Tariffs Using Monthly Data

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tariffs 1 yr.</td>
<td>$\sum_{l=0}^{11} \gamma_{CN,l}$</td>
<td>-0.079*** (0.026)</td>
<td>-0.076*** (0.028)</td>
<td>-0.018 (0.030)</td>
</tr>
<tr>
<td>ERPT 1 yr.</td>
<td>$\sum_{l=0}^{11} \beta_{I,S,l}$</td>
<td>0.219*** (0.027)</td>
<td>0.221*** (0.027)</td>
<td></td>
</tr>
<tr>
<td>PPI PT 1 yr.</td>
<td>$\sum_{l=0}^{11} \beta_{I,X,l}$</td>
<td>0.019 (0.070)</td>
<td>0.012 (0.073)</td>
<td></td>
</tr>
<tr>
<td>China Affected</td>
<td>$\phi_{CN}$</td>
<td>0.000 (0.000)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>China Not-Affected</td>
<td>$\phi_{CN}$</td>
<td>-0.000 (0.001)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Adj. $R^2$</td>
<td>0.000</td>
<td>0.003</td>
<td>0.004</td>
<td>0.004</td>
</tr>
<tr>
<td>Obs.</td>
<td>820,318</td>
<td>820,318</td>
<td>820,318</td>
<td>820,318</td>
</tr>
<tr>
<td>Sector FEs?</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

Notes: Robust standard errors in parentheses. ***, **, and * denote statistical significance at the 1, 5, and 10 percent level.

Table A1 reports the estimates of Equation (A2). The results are qualitatively consistent with those from the monthly specifications shown in Table A1. The import tariffs on Chinese goods are associated with changes in the ex-tariff import price that are economically or statistically insignificant, depending on the specification. By contrast, exchange rate passthrough in these estimates rises to roughly 38 percent.

### B.4 Tariffs on Steel Imports

Prior to the tariffs placed on Chinese imports in July 2018, the United States placed a 25 percent tariff on steel imports from all countries in March 2018. At the time, exemptions were made for imports from Argentina, Australia, Brazil, Canada, Mexico, the European Union (EU), and South Korea. By June, the exemptions were lifted for Canada, the EU, and Mexico, so June 2018 effectively brought a second wave of steel tariffs. The exemptions for the remaining countries
Table A2: Regression Analysis of Chinese Import Tariffs, Conditional on Price Changes

were made permanent. Equivalent to our analysis in Figure 1(a), therefore, we can compare import price indices – inclusive of tariffs – for steel imports from these three groups of countries.

Figure A2 shows the evolution of steel prices, which had been quite volatile during the preceding four years. The vertical lines indicate the initiation of steel tariffs for two groups of countries in March and June 2018. Steel prices from all three groups tracked each other relatively closely until the steel tariffs were introduced. After that point, prices on imports from all countries rose, but imports from the affected countries (shown in red) jumped to roughly 20 percent above those from unaffected countries.³

We summarize our import findings by noting that, whether looking at imports from China or imports of steel products, and whether looking at aggregated price indices or regression estimates that use variation across individual products, our analyses paint a similar picture of the 12-month

³For Figure A2, we allocate products into these three groupings statically, so the red dashed line drops in May 2019 simply because the US steel tariffs were dropped then for imports from Canada and Mexico. Steel imports from the EU, which were also imposed in June of 2018 and are included in that dashed red line, remain affected. Regression analyses suggest similar conclusions but estimates are imprecise given the small number of imported steel products.
Figure A2: Steel Import Price Indices, by Tariff Wave

price response to US import tariffs imposed in 2018 and 2019. Ex-tariff prices do not obviously behave differently for goods affected by trade policy compared to those that were not affected, implying the tariffs exhibited nearly complete passthrough into the total import cost and that the incidence of the tariffs lies largely with the United States.

Using the same data, methods, and time period, we estimate that the passthrough of exchange rate changes into import prices are in the range of 25 to 35 percent after one year, consistent with estimates found in a large literature, a rate much lower than the passthrough rate of tariffs into total import prices. This finding suggests being cautious when interpreting results obtained from using standard models in trade and international macroeconomics that assume a symmetric response to these two types of shocks. For example, the implications from these standard models might be more appropriately applied to longer-run outcomes, or they might be amended to allow for more uncertainty or mean-reversion in the shocks, features that might naturally explain our findings. Furthermore, as a practical matter, our result suggests that the recent depreciation of the Chinese renminbi did not offset the impact of the tariffs for US importers.
B.5 More findings on US Exports

Why did US exporters drop their prices so much more when faced with foreign tariffs than foreign exporters did when faced with US tariffs? As we noted in the paper, differences in the types of goods affected by the trade policy played a key role. We use the Rauch (1999) classification to identify differentiated goods, for which substitutes are likely more difficult to locate, and find that they account for more than 90 percent of the affected imports to the United States from China but less than half of the US exports to countries that imposed retaliatory tariffs. Relatedly, whereas affected US imports were rarely agricultural goods – goods often thought of as non-differentiated – US agriculture products accounted for roughly 10 percent of affected US exports in our sample. If undifferentiated goods are those for which import tariffs generate ex-tariff price differences, this might explain why US imports saw little or no ex-tariff price declines, while US exports suffered moderate ex-tariff price declines.

In Figures 3(a) and 3(b) we demonstrate that, in an accounting sense, undifferentiated goods and agricultural goods are those products driving the decline in US export prices.

![Graphs showing price indices for differentiated and non-differentiated goods, as well as agricultural and non-agricultural goods.](image)

(a) Differentiated and Non-Differentiated Goods  
(b) Agricultural and Non-Agricultural Goods

Figure A3: Decomposition of US Export Price Indices

To elaborate on these findings, we now consider two types of regression specifications to study US exports, analogous to what we did for the case of US imports. Our preliminary regression analysis of the first specification is consistent with the visual conclusion reached from Figure 1(b) in the paper. Specifically, we start by running the following equation with all monthly observations, including periods in which there is no price change:
\[ \Delta \ln (P_{i,j,k,t}^E) = \delta_k^E + \sum_{l=0}^{11} \gamma_l^E \Delta \tau_{k,t-l} + \sum_{l=0}^{11} \beta_l^E,S \Delta \ln (S_{j,t-l}) + \sum_{l=0}^{11} \beta_l^E,X \Delta \ln (X_{j,t-l}) + \epsilon_{i,j,k,t} \] (A3)

where we now use the superscript \( E \) to denote that the data and the relationships in equation (A3) correspond to US exports.

Table A3 reports the results from estimating (A3) on monthly data. As shown in column (1) there is about a 54 percent passthrough of the retaliatory tariff into ex-tariff US export prices after 12 months. That is, a 10 percent tariff imposed on US exports reduces US ex-tariff export prices by about 5.4 percent. The estimate reduces to 4.8 percent when controlling for other price-determining factors, as seen in column (4), which is our benchmark specification for exports included in the paper. The cumulative one-year ERPT estimates are close to 20 percent. This estimate is little changed when we simultaneously include tariff measures as a covariate. Retaliation from China accounts for about three-quarters of our observations, so in column (5), we separately estimate the one-year cumulative effect of the retaliatory tariffs for US goods exported to China and for US goods exported elsewhere. Whereas shipments to countries other than China show no statistically significant decline in the ex-tariff export price, the effect is very strong when estimated separately for China, with an estimated one-year ex-tariff export price decline of about 63 percent.
As we did in Section B.3 for imports, here we also consider a second specification that only includes non-zero price changes. We define \( \{t_0, t_1\} \) as above, estimate the following:

\[
\frac{1}{t_1 - t_0} \ln \left( \frac{P_{i,j,k,t_1}}{P_{i,j,k,t_0}} \right) = \delta_k^\varepsilon + \gamma^\varepsilon \tau_{k,t_1} + \beta_{i,k}^\varepsilon \ln \left( \frac{S_{j,t_1}}{S_{j,t_0}} \right) \\
+ \beta_{i,j}^\varepsilon X \frac{1}{t_1 - t_0} \ln \left( \frac{X_{j,t_1}}{X_{j,t_0}} \right) + \epsilon_{i,j,k,t_1,t_0}, \tag{A4}
\]

and report our results in Table A4. Here, our estimates of exchange rate passthrough rise to about 36 percent, similar to the results from import regressions conditional on a price change, as reported in Table A2. As in Table A2, we multiply the magnitude of the coefficient on tariff passthrough by 12 in order to annualize the estimates. All the estimated effects of the tariffs shown in the first row are large in magnitude and statistically significant, and column (5) makes it clear that US exports to China underlie the results. As before, we note that in comparison to the results presented in Table A3, it is not surprising that the magnitudes of these results are larger since these condition on a price change and exclude observations where the left-hand-side

\[\text{Adj. } R^2 \quad 0.000 \quad 0.001 \quad 0.002 \quad 0.002 \quad 0.002 \]

\[\text{Obs.} \quad 433,664 \quad 433,664 \quad 433,664 \quad 433,664 \quad 433,664 \]

\[\text{Sector FE}s? \quad \text{No} \quad \text{Yes} \quad \text{Yes} \quad \text{Yes} \quad \text{Yes} \]

Notes: Robust standard errors in parentheses. \(***\), **, and * denote statistical significance at the 1, 5, and 10 percent level.

Table A3: Regression Analysis of Retaliatory US Export Tariffs, Monthly Data
is zero. We conclude from Figures 1(b)-A3 and Tables A3-A4 that the retaliatory tariffs applied to US exports exhibited significantly lower passthrough than was the case for the US tariffs on imports, in large part because the US exports that were retaliated against were less differentiated compared to the goods targeted by US import tariffs.

<table>
<thead>
<tr>
<th></th>
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<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
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<tbody>
<tr>
<td>Tariffs (Annualized)</td>
<td>$12 \times \gamma^E$</td>
<td>-0.876***</td>
<td>-0.919***</td>
<td>-0.793***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.164)</td>
<td>(0.170)</td>
<td>(0.168)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>China Tariffs (Annualized)</td>
<td>$12 \times \gamma^E,_{CN}$</td>
<td></td>
<td></td>
<td></td>
<td>-0.993*</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.201)</td>
</tr>
<tr>
<td>Non-China Tariffs (Annualized)</td>
<td>$12 \times \gamma^E,_{-CN}$</td>
<td></td>
<td></td>
<td>0.405</td>
<td></td>
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<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.320)</td>
</tr>
<tr>
<td>ERPT β^E,S</td>
<td></td>
<td>0.362***</td>
<td>0.360***</td>
<td>0.361***</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.029)</td>
<td>(0.029)</td>
<td>(0.029)</td>
<td></td>
</tr>
<tr>
<td>PPI PT β^E,X</td>
<td></td>
<td>1.028***</td>
<td>1.023***</td>
<td>1.021***</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.079)</td>
<td>(0.079)</td>
<td>(0.079)</td>
<td></td>
</tr>
<tr>
<td>Adj. R^2</td>
<td>0.000</td>
<td>0.002</td>
<td>0.013</td>
<td>0.014</td>
<td>0.014</td>
</tr>
<tr>
<td>Obs.</td>
<td>66,104</td>
<td>66,104</td>
<td>66,104</td>
<td>66,104</td>
<td>66,104</td>
</tr>
<tr>
<td>Sector FEs?</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

Notes: Robust standard errors in parentheses. ***, **, and * denote statistical significance at the 1, 5, and 10 percent level.

Table A4: Regression Analysis of Retaliatory Export Tariffs, Conditional on Price Change

C Additional Retail Results

C.1 Washing Machines

Nearly all washing machine imports (other than the few exceptions mentioned above) faced tariffs, regardless of their provenance, with statutory rates ranging from 20 to 50 percent starting in January 2018. This sector has received significant attention from academics, and is the focus of Flaaen, Hortaçsu, and Tintelnot (2019), as well as from policymakers and journalists, in part because it is one of the few categories of affected goods that coincides closely with a sectoral consumer price index (CPI) provided by the BLS, namely that for “Laundry Equipment.” We obtain prices for about 700 washing machines from the private firm PriceStats as well as from the
Billion Prices Project (BPP), which collected them by scraping, at a daily or weekly frequency, the online web pages of 16 large multi-channel retailers in the United States.\(^4\) See Cavallo and Rigobon (2016) for a full description of these and closely-related data.

Figure A4: Retail Washing Machine Prices from the BPP and the CPI

![Price Indices](image1)

![Inflation Rates](image2)

(a) Price Indices

(b) Inflation Rates

Figure 4(a) shows indices for these washing machine prices from the BPP data, calculated as an equally-weighted average of good-level price changes, as well from the CPI data. The price indices are normalized to equal 1 in February 2018, the month that tariffs were imposed, as indicated with a vertical black line. Figure 4(b) shows the annual inflation rates corresponding to these indices. Prior to the imposition of these tariffs, the BPP and CPI price indices for washing machines behaved similarly and declined by about 5 percent per year. Within a few months of the import tariffs, however, both series exhibit a break, with inflation rates switching from negative to positive values for both series. In the second half of 2018, washing machine inflation was typically between 5 and 10 percent in the BPP data and between 10 and 15 percent in the CPI data. This simple evidence strongly suggests moderate to high pass-through of the washing machine tariffs to retail prices.

Underlying this high pass-through rate, however, is significant heterogeneity across different washing machine brands. Figure 5(a) plots the annual inflation rates brand-by-brand and shows that while the prices for Samsung washing machines clearly increased in response to the tariffs, the rate of inflation in Haier washers appears unchanged when comparing the pre- and post-tariff

\(^4\)Washing machines are defined as goods appearing in the data for at least one year, with product descriptions that include the words “washing machine” or “washer”, and which exclude particular disqualifying words such as “washer fluid”. As with our analyses of trade data, all our retail price analyses exclude adjacent prices that differ by more than 2.3 log points in absolute value.
periods. It may be tempting to attribute such a heterogeneous response to heterogeneity in the tariff policies. Figure 5(b) demonstrates, however, that the basic pricing patterns look the same for US brands, which likely are not directly affected by the tariffs, and for imported brands, which likely are affected.\textsuperscript{5} Consistent with the conclusions in Flaaen, Hortaçsu, and Tintelnot (2019), tariffs not only caused prices to increase for those washing machines that were affected, but also, led more generally to price hikes, including on products unaffected by the tariffs.

In the case of washing machine prices, the impact of tariffs is clear-cut, with high and rapid passthrough to retail prices. But how representative is this sector? Should we expect the same response in other sectors with large shares of products that are affected by the tariffs? To answer these questions, we next use data from the BPP and the CPI to consider the US retail prices of handbags, tires, refrigerators, and bicycles, all product categories that were significantly impacted by the tariffs on Chinese goods.\textsuperscript{6} The tariffs did not have as rapid or as obvious an impact on prices of these goods as was the case with washing machines.

\textsuperscript{5}We split these US brands (GE, Maytag, and Whirlpool) from the imported brands (Amana and Haier from China, Avanti from Denmark, Bosch from Germany, Frigidaire from Sweden, and LG and Samsung from South Korea) using online marketing reports, which may be imprecise for ascertaining the manufacturer’s country of origin. This is a useful example of the importance of analyses that use product-level information on the country of origin, which we turn to below.

\textsuperscript{6}In addition to the common discussion of these products in media coverage of the tariffs, we chose these products because they are included in product descriptions in lists of harmonized codes that identify tariffs and in product descriptions appearing on retailers’ web pages. We study 300 handbags from 12 retailers, 400 tires from 7 retailers, 5,000 refrigerators from 18 retailers, and 200 bicycles from 11 retailers.
C.2 Micro Data for Two Large U.S. Retailers

Panel A of Table A5 summarizes the resulting dataset. Our data include about 38,000 products from Retailer 1. For Retailer 2, we matched the scraped price data to the top 100,000 products by sales rank, leaving about 55,000 products. Combined, the data include more than 90,000 products covering nearly 2000 different 6-digit HS categories. Roughly two-thirds of the products, about 60,000, are imported from one of more than 80 countries. About 43,000 products are imported from China, with 30,000 of them in categories affected by the tariffs. Important for our purposes, there is significant and somewhat evenly distributed coverage across goods that are or are not in affected categories and that are or are not sourced from China.\(^7\)

<table>
<thead>
<tr>
<th>Products</th>
<th>Retailer 1 and 2</th>
<th>Retailer 1 Only</th>
<th>Retailer 2 Only</th>
<th>Imported Products</th>
<th>Household Products</th>
<th>Electronics Products</th>
</tr>
</thead>
<tbody>
<tr>
<td>Exporting Countries</td>
<td>92,624</td>
<td>37,840</td>
<td>54,784</td>
<td>59,978</td>
<td>64,421</td>
<td>10,891</td>
</tr>
<tr>
<td>HS6 Categories</td>
<td>82</td>
<td>65</td>
<td>66</td>
<td>81</td>
<td>72</td>
<td>43</td>
</tr>
<tr>
<td>Products Imported</td>
<td>1,991</td>
<td>1,651</td>
<td>831</td>
<td>1,498</td>
<td>1,406</td>
<td>781</td>
</tr>
<tr>
<td>Products Imported from China</td>
<td>59,978</td>
<td>21,144</td>
<td>38,834</td>
<td>59,978</td>
<td>46,836</td>
<td>6,679</td>
</tr>
<tr>
<td>Products in Affected Categories</td>
<td>43,490</td>
<td>13,646</td>
<td>29,844</td>
<td>43,490</td>
<td>35,748</td>
<td>3,566</td>
</tr>
<tr>
<td>Products from China &amp; Affected</td>
<td>50,460</td>
<td>23,219</td>
<td>26,241</td>
<td>40,333</td>
<td>43,505</td>
<td>6,269</td>
</tr>
</tbody>
</table>

Panel B: Pricing Behavior

<table>
<thead>
<tr>
<th>Products Without Price Changes (%)</th>
<th>Retailer 1 Only</th>
<th>Retailer 2 Only</th>
<th>Imported Products</th>
<th>Household Products</th>
<th>Electronics Products</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean Product Life (months)</td>
<td>42</td>
<td>49</td>
<td>37</td>
<td>47</td>
<td>43</td>
</tr>
<tr>
<td>Abs. Val. Price Changes (med., %)</td>
<td>11.1</td>
<td>14.3</td>
<td>10.0</td>
<td>11.4</td>
<td>10.8</td>
</tr>
<tr>
<td>Abs. Val. Price Changes, Ex-Sales (med., %)</td>
<td>9.9</td>
<td>11.4</td>
<td>8.9</td>
<td>10.0</td>
<td>9.7</td>
</tr>
<tr>
<td>Implied Duration (med., months)</td>
<td>8.9</td>
<td>9.7</td>
<td>8.5</td>
<td>9.7</td>
<td>8.5</td>
</tr>
<tr>
<td>Implied Duration, Ex-Sales (med., months)</td>
<td>10.5</td>
<td>12.7</td>
<td>9.5</td>
<td>11.2</td>
<td>11.1</td>
</tr>
</tbody>
</table>

Table A5: Summary Statistics from Two Major US Retailers

Since our analyses focus on price changes in these data, Panel B of Table A5 offers some basic summary statistics characterizing the dynamic pricing behavior of these goods. Retailer 1 has slightly stickier prices, with median price spells lasting 9.7 months, and 49 percent of products never experiencing a price change compared to corresponding respective values of 8.5 months and 37 percent for Retailer 2. Broadly, however, the two retailers exhibit similar pricing patterns. The final two columns in the table report statistics for those products that are imported, that

\(^7\) The share of Chinese goods may not be representative of the total sales made by these retailers.
are household products, and that are electronics products.\footnote{Household products are those with a 3-digit Classification of Individual Consumption According to Purpose (COICOP) starting with a “5”, and electronics products are those with a 3-digit COICOP beginning with a “9”. A given HS6 can occasionally contain both kinds of COICOPs, so some HS6 categories can have both Household and Electronics products in them. Table A5 includes some “Ex-Sales” statistics, which remove temporary price changes identified using the “Filter A” sales algorithm introduced in Nakamura and Steinsson (2008).}

Finally, for HS code classification we noted in the paper that in some cases we asked a group of research assistants to respond manually to the additional questions required by the 3CE algorithm to help refine its match. Generally, these questions could easily be answered by looking at each product’s page on the website of its retailer. When the requested information was not available online, we attempted to provide the most common or broadly representative answer possible. For example, if we were unable to answer a question about the material used to make a particular screw, we chose “steel” as that was the most common material used for screws when this information was provided. In cases where we could not visit the product’s webpage because it was no longer offered for sale, we tried to locate the product on other retailer websites and searched for a close substitute. We commonly resorted to the latter strategy. For example, if we could not find a particular 4-pack of batteries, we would look for identical batteries sold by the same retailer in a 6-pack.

\section*{C.3 Additional Retail Graphs and Regressions}

We start by using these data to plot daily retail price indices and corresponding annual retail inflation rates separately for those products imported from China that were affected by the tariffs, products imported from China that were unaffected, products not imported from China but in categories that were affected, and products not imported from China and in categories that were not affected. Looking at the price indices in Figure 6(a), or the inflation rates in Figure 6(b), it is difficult to discern any quantitatively important price differences brought about by the tariffs. The inflation rates in all groups behave similarly, though the exception may be unaffected products sold by China, as this goods sector exhibited the largest increase in inflation rates over the sample period.

To more precisely identify the differential retail pricing behavior of products impacted by the tariffs, we use these data to estimate at a monthly frequency a regression specification similar to equation (1) in the paper. We regress the change in retail prices on current and lagged tariff changes, plus fixed effects allowing for different price trends per sector and additionally different
Figure A6: Retail Price Response to Chinese Import Tariffs by Two US Retailers

trends for the total sets of Chinese products that are and are not affected by the tariffs:

$$\Delta \ln \left( P_{i,j,k,t}^{R} \right) = \delta_{k}^{R} + \phi_{CN}^{R} + \phi_{CN}^{R,\varOmega} + \sum_{l=0}^{9} \gamma_{CN,l}^{R} \Delta \tau_{CN,k,t-l} + \epsilon_{i,j,k,t}, \quad (A5)$$

where now the sectors $k$ are defined as 3-digit COICOP codes and where we no longer include information on producer prices nor on exchange rates. The results, reported in Table A6, show that while the prices for products affected by the Chinese import tariffs grow relative to the price of products in the same sector that were not affected, the difference is not stark.

The first column, also shown in the paper, estimates the regression using monthly data from both retailers for the time period running from January 2017 to July 2019. In the top row, the coefficient of 0.044 means that after one year, a 10 percentage point tariff increase on a good is associated with a 0.44 percent increase in that good’s price relative to other goods in the same sector. This estimate increases slightly, but is very similar, if we separately analyze the prices of each of the two retailers or only estimate the results for imported products (i.e. excluding those with the United States as the country of origin). When we separate products by their type, we obtain an estimate of 0.045 for household products and 0.070 for electronics products.\footnote{If we additionally include time (i.e. month) dummies, the estimates for price increases after one year go up a bit to 0.057 for all products, 0.063 for household products, and 0.073 for electronics products.}
<table>
<thead>
<tr>
<th></th>
<th>Retailers 1 and 2</th>
<th>Retailer 1 Only</th>
<th>Retailer 2 Only</th>
<th>Imported Products</th>
<th>Household Products</th>
<th>Electronics Products</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tariffs 1 yr. ( \sum_{i=0}^{R} \gamma_{CN,i} )</td>
<td>0.044*** (0.009)</td>
<td>0.049*** (0.013)</td>
<td>0.046*** (0.011)</td>
<td>0.046*** (0.009)</td>
<td>0.045*** (0.010)</td>
<td>0.070*** (0.025)</td>
</tr>
<tr>
<td>China Affected ( \phi_{CN}^{R} )</td>
<td>-0.001* (0.000)</td>
<td>-0.000 (0.000)</td>
<td>-0.001 (0.001)</td>
<td>-0.000 (0.001)</td>
<td>-0.001** (0.000)</td>
<td>-0.001 (0.000)</td>
</tr>
<tr>
<td>China Not Affected ( \phi_{CN}^{R} )</td>
<td>0.000 (0.000)</td>
<td>-0.001 (0.001)</td>
<td>0.000 (0.001)</td>
<td>0.001 (0.001)</td>
<td>-0.000 (0.000)</td>
<td>0.000 (0.000)</td>
</tr>
<tr>
<td>Adj. ( R^2 )</td>
<td>0.000</td>
<td>0.002</td>
<td>0.000</td>
<td>0.000</td>
<td>0.001</td>
<td>0.002</td>
</tr>
<tr>
<td>Obs.</td>
<td>761,402</td>
<td>282,159</td>
<td>479,243</td>
<td>484,817</td>
<td>527,119</td>
<td>71,198</td>
</tr>
<tr>
<td>Sector FE?</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

Notes: Robust standard errors in parentheses. ***, **, and * denote statistical significance at the 1, 5, and 10 percent level.

Table A6: Regression Analysis of US Retail Prices

C.4 Measurement Error

As mentioned in the paper, one might reasonably worry that measurement error in the sectoral classification algorithm is limiting our ability to identify larger differences in the retail price dynamics between products affected and unaffected by the tariffs. To look for evidence of this, we consider two subsets of our data that are the least likely to contain sectoral classification errors.

First, we exploit the fact that about one-quarter of the products were matched manually, requiring a research assistant to affirmatively check the association of a product’s text description with the HS classification. Figure A7 shows similar results to those in Figure A6. The price dynamics of all four groups of products are similar after the tariffs were put in place. Goods that are not from China and are in unaffected categories have less inflation that in our main results, but the increase in the level of inflation after the tariff increases is similar to that of the other goods.
Second, we obtained a list of products that were directly imported by Retailer 2, rather than purchased through an importer or wholesaler, so we can be confident that the retailer’s perception of the HS code is the relevant one. Nearly all of these goods were imported from China, so we only show two price indices and inflation rates in Figure A8. The Chinese goods in unaffected categories experienced more volatile inflation than those in affected categories. Their prices temporarily rose in August and September of 2018, and then temporarily fell in December 2018 (with many sale events for the holidays). Despite this price volatility, the level of inflation by early 2019 was similar for both unaffected and affected goods, consistent with our main findings.

The regressions run on these two subsets of the data do not have as much power as the full
sample, but also do not expose large differences between the affected and unaffected groups.

C.5 More International Comparisons

As noted in the paper, one possible explanation for our low retail passthrough findings is that retailers increased their margins on unaffected goods to partially offset the margin reduction on affected goods, muting any changes in their overall margins. Or, consistent with the washing machine results in Figure 5(b), perhaps tariffs enabled the producers of unaffected goods to raise their markups. Both of these cases would stabilize the relative prices of affected and unaffected products within narrowly defined sectors. Rather than inferring the impact of tariffs by comparing the prices of affected and unaffected goods within sectors, in these cases we would expect to see the prices in affected US sectors rise (compared to the overall CPI) relative to the prices in countries that did not impose tariffs on these goods.

To consider these possibilities, in Figure A9 we start by comparing the sector-level price indices for affected and unaffected sectors underlying “Commodities less food and energy” in the United States and “Goods excluding food purchased from stores and energy” in Canada, data publicly available from the US Bureau of Labor Statistics and Statistics Canada. Figure 9(a) shows the price indices for those sectors unaffected by tariffs. Before mid-2018, Canada’s

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10Based on the share of trade in the categories that is covered by the tariffs, we designate the following nine CPI sectors as “affected”: Furniture and bedding, Laundry equipment, Miscellaneous personal goods, Motor vehicle parts and equipment, Personal care products, Pets and pet products, Sewing machines, fabric and supplies, Sports vehicles including bicycles, and Tools, hardware, outdoor equipment and supplies. The remaining sectors are designated as “unaffected”. We then do our best to manually match these sectors for Canada. We use price indices that are not seasonally adjusted because some of these series for Canada are not available with seasonal adjustments.
unaffected sectors had a higher inflation rate, though the price indices for unaffected sectors in the United States and Canada are both essentially flat after the imposition of the tariffs. Figure 9(b) then compares the price indices constructed for sectors affected by the tariffs. While starting with the imposition of the tariffs, there does appear to be a moderate increase in inflation among affected categories in the United States, interestingly, this also appears to be the case in Canada, though to a lesser degree.\footnote{This analysis for the United States is reminiscent of, and largely consistent with, a widely distributed report by Goldman Sachs (2019).}

Figure A9 suggests that at least some of the price increases in the affected goods sectors may not truly reflect the tariffs, or may only reflect the general equilibrium effects of tariffs, since Canada has not imposed tariffs on imports from China. We note, however, that this analysis is highly imperfect and has limited power. The affected sectors are not chosen based on trade as a share of expenditures and do not distinguish trade from China and from other countries. Furthermore, the sectors are defined differently across the two countries, and even when the matching of sectors is good in concept, the two countries may consume very different products in practice. To avoid these issues, we next compare the prices for identical goods sold by Retailer 2 in the United States and in Canada.

We identify 2,436 products that are sold by Retailer 2 in both the United States and Canada and plot the price indices and inflation rates separately for each country, using only the retail prices for those common goods in Figure A10.\footnote{We identify identical products by looking for an exact match in model numbers, requiring that the model numbers have at least five characters. The model numbers are typically determined by the product manufacturers. They often will be identical other than the last two characters, which will be \textit{“us”} or \textit{“ca”}. We do not consider such cases to be identical products and exclude them. In total, the matched products cover 19 3-digit COICOP categories and are largely furniture products, household appliances, tools and equipment, and home repair items. We note that we did not require these goods to be available during the identical time spans in each country.} Given that the overall CPIs for the United States and Canada evolved similarly over this period, the two panels do not suggest any particularly unusual dynamics in the US prices for these goods relative to the Canadian goods over the period when the tariffs were imposed.

The patterns in Figure A10, of course, only reflect data from a single retailer. While we could not match identical goods sold in the United States and Canada for more retailers, we added pricing data for sales in the two countries for six additional retailers that operate in those two countries and sell home goods, electronics, apparel, and furniture, including two other top-10 US retailers. We selected 43 3-digit product categories and created price indices for each category,
country, and retailer. We used prices for about 350,000 products in the United States and about 120,000 in Canada. We then use equal weights for each retailer and the same average sectoral expenditure weights for both countries to generate US and Canadian price indices for these goods, where any differences can be thought of as reflecting within-retailer and within-category differences in inflation across the two countries. The results, plotted in Figure A11, again do not obviously reveal that retailers raised prices for their US customers relative to their Canadian customers, even for the same set of goods. We conclude that retailer profit margins absorbed at least a moderate amount of the adjustment to the import tariffs.

Finally, we note that while we observe very high passthrough of tariffs to the import price at the economy-level, our retail results largely reflect prices set by the largest firms. It is possible
that in terms of their negotiating power as buyers, these giant retailers differ from the average retailer and this difference may contribute to our finding of surprisingly modest passthrough to their retail prices. When we restrict our analysis of import tariffs on Chinese goods to firms with two or more subdivisions reporting to the BLS – a proxy for large firms – the estimate corresponding to ”Tariffs 1 yr.” in column (4) of Table A1 decreases to -0.112 and is statistically significant at the 10 percent level.

D Additional Front-Loading Results

The results for Figure 4 in the paper are very similar if we plot shipping containers or USD values instead of metric tons. This is shown in Figure A12, confirming that these two retailers engaged in some front-running behavior ahead of the tariffs and also were able to partially adjust in part by shifting to other countries as suppliers.

![Figure A12: Front-Running and Trade Diversion by Two Major US Retailers - Alternative Metrics](image)

We also note that these two retailers are large firms that might have more working capital and an easier time importing goods to build up inventories. An open question is the extent to which this pattern applies to the rest of the US retail sector.
References


