The Contribution of Imports to Consumer Prices*

Omar Barbiero and Hillary Stein

Federal Reserve Bank of Boston

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Abstract

We develop a new methodology for tracing out how border price increases pass through into US consumer prices. We build a model with a network structure, markups, and domestic retailers, from which we map each model object to publicly-available US data. We calculate import price sensitivities by expenditure category, which lends itself to several applications. First, we build a consumption-weighted import price index that improves prediction of consumer prices. Second, we predict the partial-equilibrium effects of various tariff scenarios and use these predictions to show that the 2018 US tariffs fully passed through to consumer prices.

Keywords: tariffs, inflation, import prices, indirect imports
JEL Codes: F40, E65, E31

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Introduction

How do border price fluctuations impact consumer inflation? While it is clear that, at least in a partial-equilibrium framework, border price increases should pass through to US consumer prices to some degree, there has been little work to date that maps and measures the effects of price changes of imported goods on the retail prices of consumption goods.

Our paper develops a new methodology for tracing out how import border price increases may pass through into US consumer prices. Our methodology brings together two key insights. First, assessing how import prices affect US consumers requires looking beyond direct consumer purchases of imported products; domestically-produced goods also contain imported components. Second, due to often large producer and retail markups, it is of immense consequence to take into account how markups respond to cost changes of imported components.

Our methodology follows from a static open economy model of domestic firms that use intermediate domestic and foreign goods, along with domestic labor, in a network structure. In order for the model, which is similar to that of Baqaee and Rubbo (2023) and Silva (2024), to better map to the data, we explicitly add in markup and retailers. Specifically, we add domestic retailers that bundle domestic final goods, foreign final goods, and domestic labor. We carefully lay out how each model object maps to official, publicly-available US data.

Our methodology allows us to construct import price sensitivity matrices, which map the purchaser price sensitivity of each consumer expenditure category to changes in the foreign price of each underlying commodity. We show that 10 percent of personal consumption expenditure (PCE) was imported in 2023, and we break down this overall share by expenditure category.

Our calculated import sensitivities, along with category-level price changes, allow us to build a consumption-weighted import price index. We show how this index outperforms the BLS Import Price Index excluding fuel and food in predicting future inflation, especially at shorter-term horizons of one and three months.

Importantly, we use our methodology to understand the pass-through of tariffs on consumer prices, under different markup response assumptions. Using census data, we calculate the share of each commodity that is imported from each country, allowing us to predict the effect, for any given tariff, on each consumer expenditure category. We use this to simulate the partial-equilibrium effect of tariff shocks on consumer prices under a number of different scenarios. We find that when margins remain constant in percentage terms, i.e. under full pass-through, tariffs can have almost double the effect relative to when margins remain constant in dollar terms. This is because the network effects of an upstream tariff propagate downstream, with each producer charging an additional percent markup on top of increased suppliers' costs. As an example, we consider the tariffs imposed by the United States in 2018. We find that they would have increased PCE inflation by 0.08 percentage points under constant-dollar markup and by 0.16 percentage points under constant-percent markup. Furthermore, we simulate the partial-equilibrium effect of an additional 10 percent tariff on all countries in the world and also on various countries individually. We find that the tariff on all countries would prompt a 0.78 to 1.34 percentage point increase in inflation, with significant heterogeneity when we consider different countries.

We then ask the question, how well do our predicted shocks correspond to actual price changes? We answer this question using the 2018 tariffs. The first rounds of tariffs impacted washing machines, aluminum, and steel, while tariffs placed between July and September impacted goods imported from China. It has been particularly hard for the economic literature to estimate the effects of 2018 tariffs on consumer prices (Cavallo et al., 2021). This is because the ways in which a tariff increase impacts the final consumer is complex and hard to measure, and micro-level studies based on difference-in-difference methodology are bound to have negative omitted variable bias. For example, suppose that we conduct a difference-in-differences comparison between prices of Chinese shoes and of domestically-produced shoes around an enactment of tariffs on Chinese shoes, and suppose that we compare prices of the two shoe types within specific retail companies. Negative omitted variable bias will arise from this strategy in two ways. First, goods imported by domestic producers of shoes use (directly and indirectly) materials that are in turn impacted by tariffs. This will inflate the price of the "control" group. Second, the protectionist effect of tariffs in the shoe market will endogenously increase prices of domestically produced shoes, given the high degree of substitution within the shoe industry. For both of these reasons, a cross-industry difference-in-differences approach is more likely to have correct estimates. This is because we can account for input output linkages between industries, and because cross-industry elasticities are lower than within-industry elasticities. Indeed, when we compare expenditure categories with various exposures around the China tariffs of 2018, we find full pass-through under our constant markup assumption. When examining the dynamics of the response, we find that prices rose significantly in the second month of tariffs and continued to rise through the beginning of 2019.

Related Literature This study contributes to a few strands of the literature. First, it contributes to and builds upon studies of inflation with production networks (Basu, 1995; Baqaee and Farhi, 2019; La'O and Tahbaz-Salehi, 2022; Rubbo, 2023; Baqaee and Rubbo, 2023; Minton and Wheaton, 2023; di Giovanni et al., 2023; Silva, 2024). These studies emphasize the importance of the interaction between sectoral price and wage rigidities and production networks in understanding inflation. Our paper carefully considers how price shocks are disseminated along supply chain networks, taking into account various markup practices.

Second, this paper contributes to the pass-through literature. There is a large literature on exchange rate pass-through (Feenstra, 1989; Goldberg and Knetter, 1997; Amiti, Itskhoki and Konings, 2014), backed up by a theoretical literature that explains variable markups through real rigidities (Kimball, 1995; Atkeson and Burstein, 2008). We most closely relate to the studies that have examined pass-through in the context of the 2018 US-China trade war. A number of studies have found that the full burden of the 2018 tariffs was paid by US importers. Fajgelbaum et al. (2019), Amiti, Redding and Weinstein (2019), and Cavallo et al. (2021) all show full-pass through at the border using US customs data. It is less clear in the existing literature how these higher border prices impacted US consumer prices. Cavallo et al. (2021) uses microdata from two large household retailers to show that these specific retailers had low pass-through of border prices to consumer prices. However, the literature thus far is unclear how consumer prices elsewhere responded. After carefully constructing exposure measures at the consumer expenditure category level (a procedure we first explained in Barbiero and Stein, 2025), we find full pass-through of tariff exposure to consumer prices.[1]

Finally, our study contributes to the literature on inflation forecasting, as reviewed in Stock and Watson (2009) and Faust and Wright (2013). Specifically, we supplement the prototypical direct forecasting model of inflation by including the BLS Import Price Index excluding fuel and food and our consumption-weighted import price index as additional regressors. We find that including our consumption-weighted import price index can improve upon a model that only uses past inflation and on a model that additionally uses the official import price index.

The paper proceeds as follows. Section 1 briefly describes our partial-equilibrium network model and explains how we map the model to the data in order to construct the import price

[1] Since the release of Barbiero and Stein (2025), a couple additional policy briefs have been written independently of the present paper. Specifically, Baslandze et al. (2025) and Minton and Somale (2025) also focus on empirical estimates of tariff pass-through on consumer prices. Baslandze et al. (2025) use micro-level data linking imports to consumer expenditures. They focus on retail categories available in their dataset. We use public data at the industry level to focus on the full effect on the US economy. Moreover, we consider the full network effects of tariffs, not only the effect related to directly affected suppliers. Minton and Somale (2025) build on the work of Barbiero and Stein (2025) to focus on the pass-through of tariffs to PCE prices. However, they do not focus on the importance of markup response assumptions; that is, they only compute the "constant-dollar" percent markup effect of Barbiero and Stein (2025). Additionally, they do not include all consumer expenditure categories. To the extent of our knowledge, our study is the first to evaluate and test the full network effects on PCE inflation under full pass-through. We also focus on a broader set of consumer expenditure categories than existing studies, in order to evaluate the full effect on the US economy.

sensitivity of expenditure categories. The next few sections go through a few applications of our methodology. Section 2 describes the import share of consumption and breaks this down by category. Section 3 presents a forecasting exercise in which we forecast inflation with the consumption-weighted import price index. Section 4 uses our import price sensitivities to simulate tariff shocks and output the partial-equilibrium inflation response to these shocks. Section 5 compares these predicted inflation outcomes to category-level inflation around the 2018 tariffs. Finally, 6 concludes.

1 Constructing the Import Price Sensitivity of Expenditure Categories

Our methodology allows us to map—dollar-for-dollar—the impact of a border price increase to the most disaggregated expenditure categories available in US consumption data. We build an intuitive static open economy model in partial equilibrium where every component can be mapped to US official public data. The mapping is a contribution in its own right, and this section will provide intuition behind the data available and the economic concepts behind them.

In the model there are two kinds of primary factors: import goods and labor. There are also two kinds of producers in the domestic economy: firms and retailers. Firms use intermediate domestic and foreign goods, as well as labor, to produce domestic final goods. Retailers bundle domestic final goods and foreign final goods with domestic retail labor to create composite retail goods. Households consume composite retail goods. Due to the market structure, both domestic goods producers and retailers incorporate sector-specific markups and costs into their prices. The model is similar to Baqaee and Rubbo (2023) and Silva (2024), except we explicitly add markup and retailers for better mapping with the data. The production network structure, the widespread presence of markups, and the division between the production and retail sector are a necessary condition to match the available US industry-level data. Appendix A contains all the details and derivation of this open economy model.

To a first-order approximation, our model shows that the impact of a vector of import price changes $\hat{P}^*$ on the vector of retail final goods price changes $\hat{P}^E$ can be decomposed into $\hat{P}^E = (\Delta^{\text{Direct}} + \Delta^{\text{Indirect}})\hat{P}^*$, where

$$\text{Direct Sensitivity:} \quad \Delta^{\text{Direct}} = M^E \Theta^* \tag{1a}$$

$$\text{Indirect Sensitivity:} \quad \Delta^{\text{Indirect}} = M^E \Theta (\mathbb{I} - M\Omega)^{-1} M \Omega^*. \tag{1b}$$

The direct sensitivity is the predicted response to an import price increase of consumer prices due to the share of personal expenditures in foreign *final* goods. The indirect sensitivity is the predicted response of consumer prices due to the share of domestic final goods consumption that uses imported intermediate goods in production processes.

We now unpack the intuition behind each component in equations (1a) and (1b), and we show how to map these objects to the data.[2] Our data comes from a number of publicly-available tables from the US Bureau of Economic Analysis (BEA) Input-Output Accounts: the Use Tables, the Make Tables, the Import Matrices, and the PCE bridge.[3]

- Θ and Θ^* are the domestic and foreign goods retail aggregation matrices, respectively. They are $E \times N$ matrices (where E is the number of retail goods, and N is the number of final goods) containing the sales-based shares of domestic or imported products, respectively, purchased by retailers to produce each retail good.

  In practice, Θ and Θ^* must be built by merging a few separate BEA datasets. First, the shares of domestic and imported commodities in final demand are calculated from the Use Tables and Import Matrices. (In this paper, we use the terms "commodity" and "final good" interchangeably—both are the direct inputs into the retail sectors, but "commodity" is the term used in the BEA data.) Specifically, each table has a column containing final demand, either in total or for imports, of each commodity in producers' prices. Second, these (BEA code) commodities are concorded to each retail-level (NIPA code) final expenditure category using the PCE Bridge.

- Ω and Ω^* are the domestic and import expenditure matrices, respectively. They are $N \times N$ matrices, where each cell Ω^x_{ij} contains the share of domestic or foreign commodity j used to produce the domestic commodity i. In practice, Ω and Ω^* are built by starting with the domestic and foreign direct requirement matrices, respectively, which show the input of each commodity required per unit of gross output of each industry. These matrices are obtained from the commodity-by-industry Domestic Use Table and Import Table and are normalized by industry gross output. Both matrices must then be multiplied by the proportion of total output of each commodity produced in each industry, obtained from the Make Table, converting these matrices into square commodity-by-commodity matrices.

- M^E is the retail markup matrix. It is an $E \times E$ diagonal matrix containing retail-level markups specific to each retail sector. Under full pass-through (described in more detail

[2]See Appendix B for more details.

[3]In all cases, we use the 'after redefinition' versions of the tables.

below), M^E is built starting from the PCE Bridge, which gives the value added of each retail sector from each commodity by listing both producer and purchaser prices. Furthermore, this dataset decomposes this value added into the contribution of the transportation, wholesale, and retail sectors. We net employee compensation from the value added of each of these three sectors using information from the Use Tables.

- M is the commodity markup matrix. It is an $N \times N$ diagonal matrix containing commodity-level markups specific to each domestic production sector. Under full pass-through, M is computed by dividing gross output by the total variable costs of each commodity, all obtained from the Use Table.[4]

We can now see how the direct sensitivity is thus the share of expenditure of foreign final goods within each retail category, augmented by the size of the markup in each retail category. Additionally, we can interpret the the indirect sensitivity as the amount of imported cost increases for intermediate purposes (that is, $M\Omega^*$), propagated through the domestic Leontief matrix (that is, $(\mathbb{I} - M\Omega)^{-1}$) and bundled into domestic retail goods (that is, $M^E\Theta$). In practice, these sensitivities are year-specific, but we omit the time subscript for simplicity.[5]

In our sensitivity calculations, we use two main competing pass-through assumptions:

- **Constant Percent Markup** (or full pass-through): domestic markups over marginal costs are assumed to be constant in percentage terms, according to the standard benchmark in the economic literature. We allow for production sector and retail-sector specific markups by populating the matrices M and M^E as described above.

- **Constant Dollar Markup** (or partial pass-through): domestic profits are assumed to be constant in nominal value after an import price increase. Under this assumption, markup can be considered a domestic factor of production that is exogenous to import price changes. This is equivalent to assuming partial pass-through because profits *decrease* in percentage term over marginal costs, but not enough to fully absorb the impact of additional costs for the consumer. An additional appealing feature of this assumption is that the import sensitivity matrices above can be interpreted as shares of imported value in final expenditure. In practice, we substitute the markup matrices M and M^E with identity matrices to deliver this case.

Finally, we define the importance-weighted PCE sensitivity matrix as

$$\Delta^w = W^c(\Delta^{\text{Direct}} + \Delta^{\text{Indirect}}), \tag{2}$$

[4] Specifically, total variable costs are the sum of salaries and cost of materials.

[5] Appendix B provides specific information on how we calculate sensitivities for each year.

where W^c is a diagonal matrix with diagonal values defined as the share of each PCE category in total PCE. Aggregating the importance-weighted sensitivity by imported commodity, as in $\mathbf{1}^\top \Delta^w$, gives the aggregate sensitivity of personal consumption expenditures to each imported commodity. Aggregating the importance-weighted sensitivity by expenditure category, as in $\Delta^w \mathbf{1}$, gives the "importance-weighted" sensitivity to total imports of each expenditure category.

2 Import Shares

Our import sensitivities under the constant-dollar markup (partial pass-through) assumption can be reinterpreted as the share of US PCE that is imported.[6] Summing across all PCE categories, we find that 6 percent of PCE was directly imported in 2023, and 4 percent was indirectly imported. In total, spending on direct and indirect imports accounted for 10 percent of total PCE.[7] This percentage includes US components of foreign goods and services that are then imported into the US.

These shares have been relatively consistent over the past two decades. Our methodological framework enables us to break down these shares into underlying input commodities or expenditure categories. Figure 1 shows the contribution of both direct and indirect imports to PCE, broken down by NIPA expenditure category, and weighted by their PCE importance as in equation 2. For example, *direct* imports of pharmaceutical and other medical products account for 0.65 percent of PCE. Spending on *indirect* imports used in the domestic production of pharmaceutical and other medical products comprises 0.16 percent of PCE. Total imports—the sum of the direct and indirect components—in pharmaceutical and other medical products consumption account for 0.81 percent of PCE. The chart also highlights that some expenditure categories, such as hospital and nursing home services, may use a lot of indirect imports, though those services tend to be domestically produced.

3 Forecasting Inflation with the Consumption-Weighted Import Price Index

We exploit our methodology to build an alternative import price index, tailored to estimate the effect of import prices on final consumption. To do so, we build a concordance matrix

[6] Under the constant-dollar markup assumption, markups do not change in dollar terms with import price changes, and thus can be thought of as a domestic factor of production.

[7] Our calculation of the import contribution to PCE is similar but not equivalent to that of Hale, Hobijn and Fernanda Nechio (2019), who estimate that 11 percent of headline PCE can be traced to imported goods.

between the most disaggretaed industry import codes available from the Bureau of Labor Statistics (BLS) import price and index and BEA commodity codes. Define such matrix concordance matrix as C. Then, our PCE import price index is defined as:

$$\text{IPI}_t^{\text{PCE}} = \mathbf{1}^\top W_{t-12}^c (\Delta_{t-12}^{\text{Direct}} + \Delta_{t-12}^{\text{Indirect}}) C \hat{p}_t^*$$

where $\hat{p}_t^*$ is a vector containing disaggregated values of the import price index from the BLS for month t. The sensitivity shares date to the previous year's share to map closely to how the aggregate price import is computed by the BLS.

Given that we use exactly the same underlying time series $\hat{p}_{m,t}$ as the BLS to compute our import PCE index, our methodology only differs in the relative weighting given to different sectors. Why do we expect a better performance from our index? Unlike our index, where weights are based on the import price sensitivity of consumption, the BLS import price index weights goods with trade dollar value shares. However, goods are imported not only for final consumption or as an intermediate for final consumption production—imports are also used for government expenditure, investment, exports, and more.

In order to assess the forecasting ability of our consumption-weighted import price index, especially compared to the BLS Import Price Index excluding fuel and food (which we refer to as the "core" BLS import price index), we implement h-month-ahead forecasts of core PCE with both indices, re-estimating the model every month from 2012m1 until today:

$$p_{t+h} - p_{t+h-1} = \alpha + \beta(z_t - z_{t-1}) + \sum_{j=0}^{11} \alpha_j (p_{t-j} - p_{t-j-1}) + \varepsilon_{t+h}, \tag{3}$$

where p denotes the log core PCE price index in a given month and z denotes the relevant index. We compare our index against the core BLS import price index to allow for a closer mapping into the core PCE. For various horizons of $h = 1, 3, 6, 12$ months we then report the additional R^2 that our model delivers via an alternative model:

$$p_{t+h} - p_{t+h-1} = \alpha + \sum_{j=0}^{11} \alpha_j (p_{t-j} - p_{t-j-1}) + \varepsilon_{t+h}. \tag{4}$$

We also report the RMSE ratio between our baseline model, Equation 3 where z denotes our consumption-weighted import price index, and the competing model, Equation 3 where z denotes the core BLS import price index. Finally, we run a Diebold-Mariano test between these two competing models and report the test statistic and p-value.

Results are reported in Table 1. We can see that at all four horizons, our baseline model outperforms the competing model where our consumption-weighted import price index is replaced with the core BLS import price index. For horizons of 1 and 3 months, this outperformance is statistically significant.

4 Simulations of Tariff Shocks

Beside offering a one-to-one mapping between imports and personal consumption expenditure, our methodology offers a straightforward tool to study the inflationary effect of specific tariff episodes. In this section, we outline the importance of the markup assumption response in determining the total impact on PCE inflation. Additionally, we show how our methodology is a useful tool to intuitively assess the impact of tariff exemptions, a feature of most tariff reforms.

To do so, we build a concordance matrix between product codes available from border declarations and BEA commodity codes. We define F as a matrix containing the share of country-product specific value of import for each BEA comodity. Each column represents a country-10 digit HTSUS product code combination, while each row represents one of the 402 BEA commodities. We can then use a country-product specific vector of tariffs τ_t at any given time to predict the aggregate tariff effect as:

$$\hat{P} = \mathbf{1}^{\top} W^{c} (\Delta^{\text{Direct}} + \Delta^{\text{Indirect}}) F \tau \tag{5}$$

The foreign trade concordance matrix F offers a convenient bridge to simulate the effects of tariffs or border shocks τ starting at the most disaggregated level possible.[8] Such level of disaggregation in the tariff scenario τ allows us to account for exemptions, which are usually set at the 10-digit HTSUS-country level by law. Our methodology allows for an exempted category to both have a direct (null) effect on consumption purchases via Δ^{Direct} and an indirect (null) effect via the domestic supply chain.[9]

We show the effect of different tariff scenarios under our two main markup response assumptions introduced in Section 1: "constant-dollar markup" for partial pass-through and "constant-percent markup" for full pass-through. Our estimates assume that the full burden of the tariffs is paid by US importers, consistent with what was observed with the tariff increases that were imposed in 2018 (Fajgelbaum et al., 2019; Amiti, Redding and Weinstein, 2019; Cavallo et al., 2021).

[8] As in the previous sections, all of these matrices are year-specific but we omit the time subscript for clarity.

[9] For example, say that mechanical components are exempted from a certain tariff but steel is not exempted. This methodology would account for the fact that the final price of mechanical components should still go up due to the increased price of steel, to the extent that steel is used to produce mechanical components.

We assess a number of scenarios. First, we use the cumulated effect of all tariffs introduced on US imports in 2018.[10] We find a predicted partial-equilibrium effect on headline PCE inflation of 0.08 percentage points under constant-dollar markup or 0.16 percentage points under constant-percent markup. Most of the effect comes via the indirect channel, that is, from higher costs of US domestic producers. This may be why previous literature has struggled to find a pass-through of these tariffs into consumer prices (Cavallo et al., 2021). In the next section, we show how these estimates find empirical confirmation in cross-sectional PCE response.

Second, we assess a hypothetical uniform 10 percent tariff applied to all imports. We find this scenario leads to an increase in headline PCE prices of 0.78 percentage points under constant-dollar markup or 1.34 percentage points under constant-percent markup. When we examine a uniform 10 percent tariff on all imports but with a US content exemption, we find this exemption makes only a marginal difference of 0.1 to 0.2 percentage points.[11] Specifically, we find an increase in headline PCE prices of 0.68 percentage points under constant-dollar markup or 1.18 percentage points under constant-percent markup

There are two notable results from our scenario analysis. First, given the importance of markups in the data, assuming constant-percent markup can almost double the predicted effect over assuming constant-dollar markup. Second, we find that the increased effect under constant-percent markup mostly acts through indirect effects. The intuition is that an upstream marginal cost increase due to a tariff is amplified along the supply chain, as each producer charges a constant-percent markup on top each respective input purchase. This outsized effect from domestic markups on indirect imports is particularly visible when we disaggregate such effects by source country.

Figure 2 shows the decomposition of a 10 percent uniform tariff with US-content exemption by goods' origin country. All effects are weighted by the importance of each category within total PCE. China is the top source of the inflationary effect, mostly due to direct purchases form consumer. However, the indirect effect becomes more important under the constant-percent markup assumption. Canada and Mexico are also important inflationary sources under a 10 percent tariff, and this is despite the tariff discount on USMCA-compliant goods.

Note that our methodology implies that the effect grows linearly to the simulated tariff

[10] These tariffs, and related exemptions, were provided by Fajgelbaum et al. (2019) at the country-product level.

[11] Under this exemption, the tariff is not applied on the percentage of value added originated in the US. This is a typical exemption included in most executive orders introduced by the Trump administration in 2025. Our methodology can easily account for such exemption using the OECD input-output tables. In particular we discount for the US-content in each country's export to the US. These shares can vary widely for each country-product combination. For the case of Canada and Mexico we use the share of USMCA-compliant goods instead.

vector τ (conditional on the markup assumption). For instance, since Figure 2 implies that a 10 percent tariff with US-discounted content on Chinese goods has a 0.12 to 0.21 percentage point effect on PCE inflation, a similar 20 percent tariff will have an effect between 0.24 to 0.42 percentage points.

5 Past Tariff Shocks Pass-through into Consumer Prices

As discussed in the previous section, our methodology allows us to predict the effect of tariff shocks on PCE inflation in a partial-equilibrium framework. It is natural to then ask, how have our predicted shocks, based on calculated import price sensitivities, actually passed through to PCE in past episodes? The answer may provide validating evidence for our markup assumption.

To answer this question, we zoom in on the 2018 tariffs and focus on NIPA expenditure groups individually.[12] Specifically, we focus on the China tariffs enacted between July and September 2018. We collapse the different waves of tariffs into one tariff shock, and we run a difference-in-difference specification in which we compare year-over-year price changes of expenditure categories with various predicted tariff effects. Formally, we run the following regression model:

$$\pi_{i,t} = \alpha_i + \delta_t + \beta \text{Post-Period}_t \times s_i + \gamma \hat{w}_{i,t-1} + \varepsilon_{i,t}, \tag{6}$$

where π denotes the year-over-year price change,[13] s denotes the predicted effect for NIPA expenditure category i (as explained in Section 4), and $\hat{w}$ denotes the year-over-year wage change and is included as a control variable.[14] Predicted effects are calculated using the tariff data in Fajgelbaum et al. (2019). i refers to the NIPA expenditure category and t refers to the monthly date. The post-period begins in July 2018, and our sample runs from July 2017 through April 2019. We choose this end date so as not to contaminate with the tariffs put on China starting in May of 2019. Our regression also includes NIPA and time fixed effects. The key parameter of interest is β, which approximates pass-through. A coefficient of one would indicate full-pass through for a given markup assumption.

Results are shown in Table 2. We can see that for goods, there seems to have been full pass-through using the constant-percent markup assumption, shown by the significant

[12]The analyses in this section use NIPA expenditure groups at the level shown in Figure 1.

[13]We take year-over-year price changes to control for seasonality.

[14]The wage control come from the CES seasonally-adjusted average hourly earnings data. The data is at the NAICS level, so in order to get it to the NIPA-level, we follow a similar procedure to the one outlined in subsection B.4.

coefficient of 0.968, only slightly less than one. If we use the constant-dollar assumption, pass-through would seem higher than one. This is evidence in favor of our constant-percent markup assumption, even though we cannot reject the hypothesis that the constant-dollar coefficient is statistically different than one. When we turn to services, we see weaker results, with positive but insignificant coefficients.

We next estimate effects each month during the sample period in order to better understand the dynamics of the response. Specifically, we run the following regression:

$$\pi_{i,t} = \alpha_i + \delta_t + \beta_t^{\text{Direct}} s_i^{\text{Direct}} + \beta_t^{\text{Indirect}} s_i^{\text{Indirect}} + \gamma \hat{w}_{i,t-1} + \varepsilon_{i,t}, \tag{7}$$

where predicted effects are now only calculated using the constant-percent markup assumption and where we include expenditure categories for both goods and services. Additionally, these regressions separate predicted effects from direct and indirect tariff exposure in order to better compare the two and understand the timing of each.

Results are shown in Figure 3; panel (a) shows the coefficient on the predicted direct effect over time, and panel (b) shows the coefficient on the predicted indirect effect. We can see significant results from the direct effect starting in September 2018, with prices continuing to rise for effected expenditure categories through the beginning of 2019. The magnitude of the coefficient hovers around one, which suggests full pass-through under the constant-percent markup assumption. We can also see that, for the most part, the parallel trends assumption seems to hold, though there may have been anticipation effects in April 2018.[15] The indirect effect appears later, with significant results starting in December 2018. The coefficient on the indirect effect is large, but so are standard error bars. This makes sense given we would expect more noise as tariffs work their way through the supply chain.

6 Conclusion

In this paper, we study the effects of import prices at the border on US consumer prices. We do so by developing a new methodology, which builds off a static open economy model of firms that use domestic and foreign goods in a network structure, to which we add markups and retailers. We carefully map each model object to official, publicly-available US data, thus building matrices that show the sensitivity of each consumer expenditure category to import price changes in underlying commodities.

We show how these matrices allow us, as well as future researchers, to do a number of

[15]The uptick in 2018 may also have been caused by contamination by earlier tariffs: the washing machine tariffs enacted in February 2018 and the steel and aluminum tariffs enacted between March and June 2018.

things. First, we can use them to understand the percent of PCE that is imported, and we can break this down into expenditure category and into direct and indirect imports. Second, we can calculate a consumption-weighted import price index, which we show outperforms the BLS "core" import price index in inflation forecasting. Third, we can assess the partial-equilibrium effect of various tariff scenarios, a crucial tool for policymakers and business leaders as tariff schedules are updated. Finally, we show that when we use our network mapping between import prices and retail prices, we find full pass-through from the 2018 tariffs to consumer prices.

References

Amiti, Mary, Oleg Itskhoki, and Jozef Konings. 2014. "Importers, Exporters, and Exchange Rate Disconnect." *American Economic Review*, 104(7): 1942–1978.

Amiti, Mary, Stephen J. Redding, and David E. Weinstein. 2019. "The Impact of the 2018 Tariffs on Prices and Welfare." *Journal of Economic Perspectives*, 33(4): 187–210.

Atkeson, Andrew, and Ariel Burstein. 2008. "Pricing-to-Market, Trade Costs, and International Relative Prices." *American Economic Review*, 98(5): 1998–2031.

Baqaee, David, and Elisa Rubbo. 2023. "Micro Propagation and Macro Aggregation." *Annual Review of Economics*, 15:91-123.

Baqaee, David Rezza, and Emmanuel Farhi. 2019. "The Macroeconomic Impact of Microeconomic Shocks: Beyond Hulten's Theorem." *Econometrica*, 87(4): 1155–1203.

Barbiero, Omar, and Hillary Stein. 2025. "The Impact of Tariffs on Inflation." *Federal Reserve Bank of Boston Current Policy Perspectives*, 25(2).

Baslandze, Salome, Simon Fuchs, KC Pringle, and Michael Dwight Sparks. 2025. "Tariffs and Consumer Prices." *Federal Reserve Bank of Atlanta - Policy Hub.*

Basu, Susanto. 1995. "Intermediate Goods and Business Cycles: Implications for Productivity and Welfare." *The American Economic Review*, 85(3): 512–531.

Cavallo, Alberto, Gita Gopinath, Brent Neiman, and Jenny Tang. 2021. "Tariff Pass-Through at the Border and at the Store: Evidence from US Trade Policy." *American Economic Review: Insights*, 3(1): 19–34.

di Giovanni, Julian, Şebnem Kalemli-Özcan, Alvaro Silva, and Muhammed A. Yıldırım. 2023. "Pandemic-Era Inflation Drivers and Global Spillovers." *Federal Reserve Bank of New York Staff Reports.*

Fajgelbaum, Pablo D, Pinelopi K Goldberg, Patrick J Kennedy, and Amit K Khandelwal. 2019. "The Return to Protectionism." *The Quarterly Journal of Economics*, 135(1): 1–55.

Faust, Jon, and Jonathan H. Wright. 2013. "Chapter 1 - Forecasting Inflation." In *Handbook of Economic Forecasting.* Vol. 2, , ed. Graham Elliott and Allan Timmermann, 2–56.

Feenstra, Robert C. 1989. "Symmetric pass-through of tariffs and exchange rates under imperfect competition: An empirical test." *Journal of International Economics*, 27(1): 25–45.

Goldberg, Pinelopi Koujianou, and Michael M. Knetter. 1997. "Goods Prices and Exchange Rates: What Have We Learned?" *Journal of Economic Literature*, 35(3): 1243–1272.

Hale, Galina, Bart Hobijn, and Doris Wilson Fernanda Nechio. 2019. "How Much Do We Spend on Imports?" *FRBSF Economic Letter*, 2019-10.

Kimball, Miles S. 1995. "The Quantitative Analytics of the Basic Neomonetarist Model." *Journal of Money, Credit and Banking*, 27(4): 1241–1277.

La'O, Jennifer, and Alireza Tahbaz-Salehi. 2022. "Optimal Monetary Policy in Production Networks." *Econometrica*, 90(3): 1295–1336.

Minton, Robbie, and Mariano Somale. 2025. "Detecting Tariff Effects on Consumer Prices in Real Time." *FEDS Notes*.

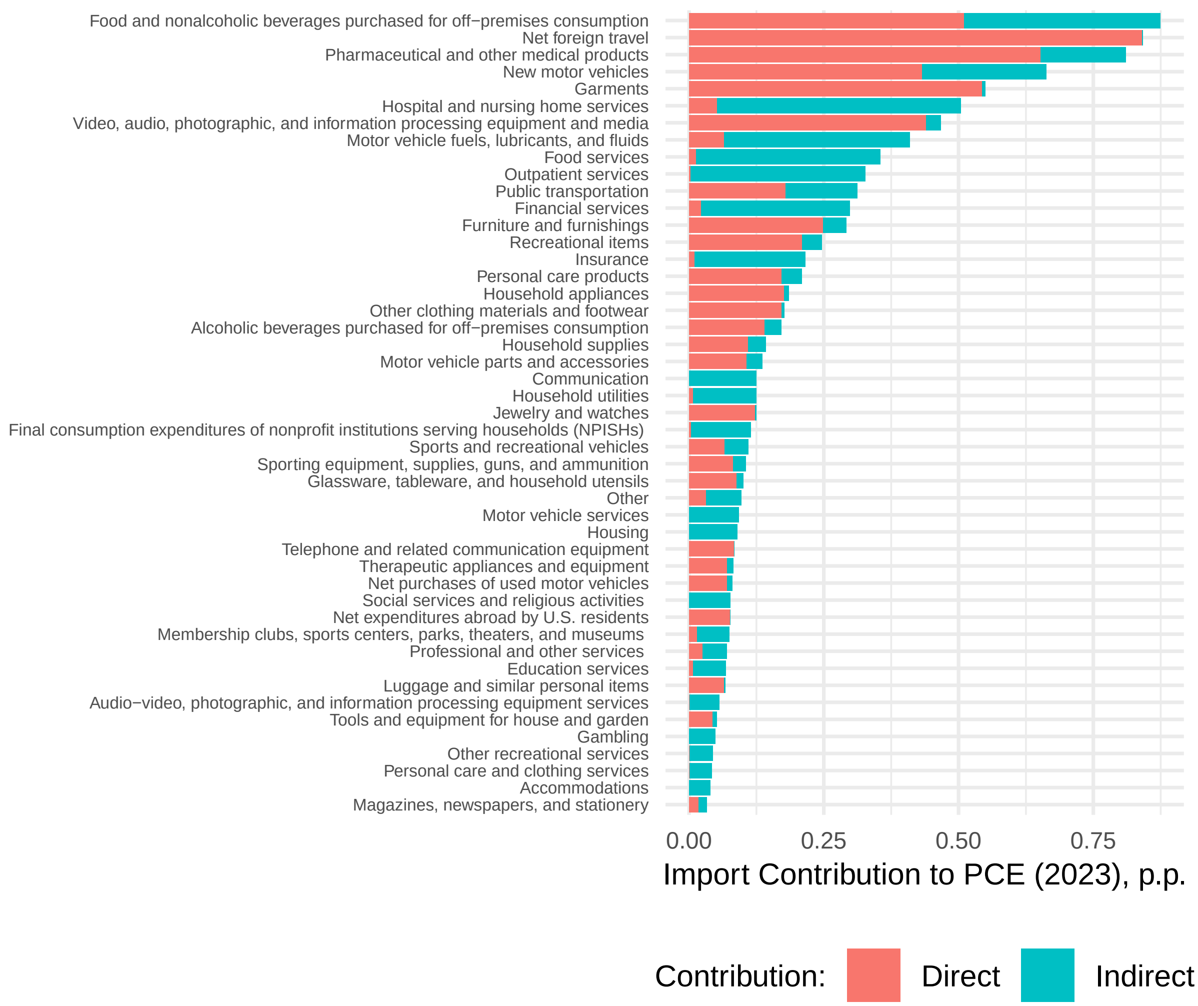
Minton, Robert, and Brian Wheaton. 2023. "Delayed Inflation in Supply Chains: Theory and Evidence."

Rubbo, Elisa. 2023. "Networks, Phillips Curves, and Monetary Policy." *Econometrica*, 91(4): 1417–1455.

Silva, Alvaro. 2024. "Inflation in Disaggregated Small Open Economies."

Stock, James H., and Mark W. Watson. 2009. "Phillips Curve Inflation Forecasts." In *Understanding Inflation and the Implications for Monetary Policy: A Phillips Curve Retrospective.* , ed. Jeff Fuhrer, Yolanda K. Kodrzycki, Jane Sneddon Little and Giovanni P. Olivei, 99–202. Cambridge: MIT Press.

Figure 1: PCE Shares of Imports, by Expenditure Category



Notes: The red bars show the share of PCE corresponding to imported goods that are directly consumed by US households. The blue bars show the share of PCE corresponding to imports that are used as inputs in domestic production. We use the national income and product accounts (NIPA) categories of goods and services. *Sources*: BEA, authors' calculations.

Table 1: The Predictive Power of Import Prices on Core PCE Inflation

			Diebold-Mariano Test	
Horizon	Additional R2	RMSE Ratio	Statistic	p-value
1	0.0191	0.964	-2.173	0.0298
3	0.0121	0.978	-4.153	0.0000
6	0.0010	0.979	-0.627	0.5309
12	0.0007	0.974	-1.612	0.1069

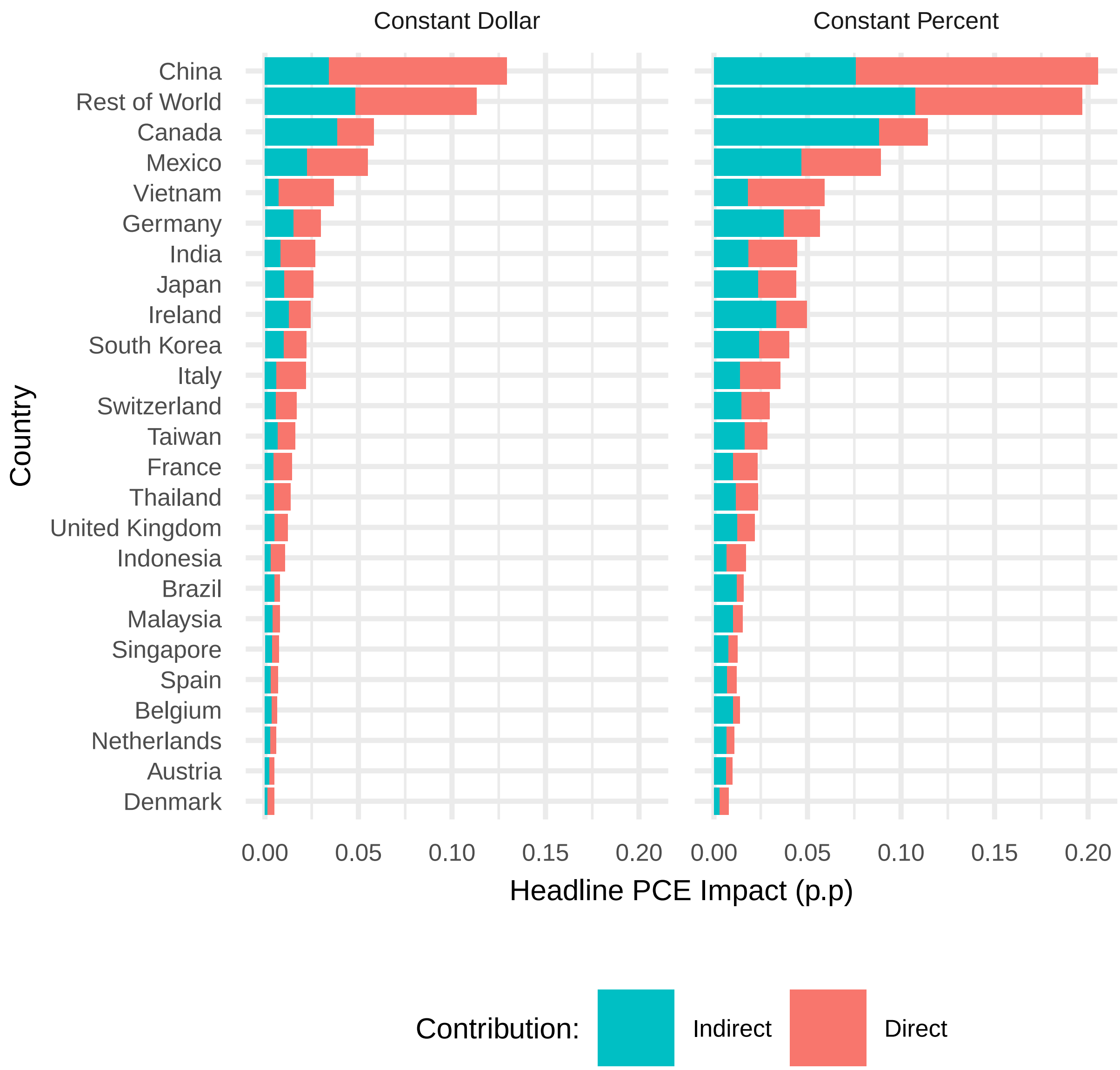
Notes: Additional R2 is the difference between the R2 of the model using our index and the R2 of the model without an additional predictor z. RMSE is the square root of the average prediction error; the RMSE ratio is the ratio of the RMSE of the model with our index versus the RMSE of the model with the "Core" BLS import price index. The null hypothesis of the the Diebold-Mariano test is that a variable has the same forecast accuracy of the "Core" BLS import price index. A negative statistic indicates that the model with our index is our better predictor. *Sources*: BEA, BLS, authors' calculations.

Table 2: Pass-through Depending on Markup Assumption

	Goods		Services	
	(1)	(2)	(3)	(4)
Post-period × Predicted Effect	0.968**		0.621	
Assumption: Constant-Percent	(0.434)		(1.237)	
Post-period × Predicted Effect		1.253**		1.252
Assumption: Constant-Dollar		(0.600)		(1.680)
Wage change	-0.001	-0.002	0.004	0.005
	(0.029)	(0.029)	(0.035)	(0.037)
NIPA FE	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
R^2	0.644	0.643	0.690	0.690
R^2 within	0.024	0.023	0.006	0.007
N	594	594	506	506

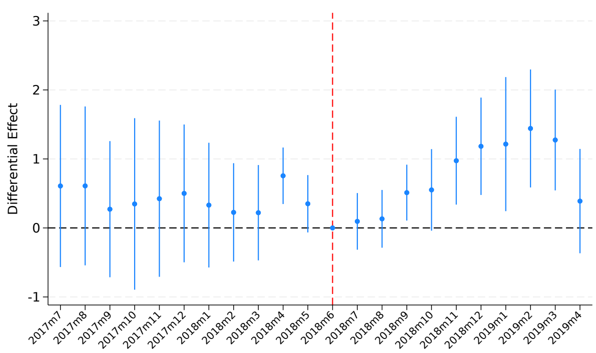
Notes: This table examines pass-through from the China tariffs enacted between July and September 2018. The post-period begins in July 2018, and our sample runs from July 2017 through April 2019. Standard errors are clustered at the NIPA expenditure category level. *Sources*: BEA, BLS, Fajgelbaum et al. (2019), authors' calculations.

Figure 2: Source country Decomposition of a 10% Uniform Tariff with US-content exemption

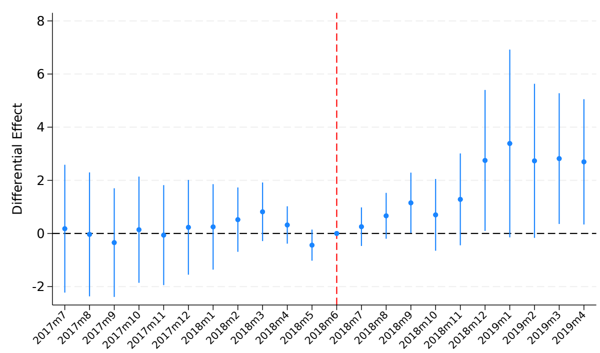


Notes: Each line represents the country-specific contribution to the total PCE tariff effect computed as in equation (5) where $\tau = (\mathbf{1} - s^{\text{US}}) \oslash 10\%$. s^{US} is the US content in US imports computed for each country-ISIC product combination from the OECD 2020 TiVA database. We use the share of USMCA imports to discount the tariff effects for Canada and Mexico instead.
Sources: US Bureau of Economic Analysis, US Census Bureau, and authors' calculations.

Figure 3: Estimated Pass-through of 2018 China Tariffs



(a) Direct



(b) Indirect

Notes: This figure examines pass-through from the China tariffs enacted between July and September 2018. Panel (a) shows the coefficient on the predicted direct effect, and panel (b) shows the coefficient on the predicted indirect effect. Standard errors are clustered at the NIPA expenditure category level. The dotted red line shows the last month before the post-period. The blue bars give 90% confidence intervals. *Sources*: BEA, BLS, Fajgelbaum et al. (2019), authors' calculations.

A Model

To help interpret our methodology and its assumptions we build a static open economy model in partial equilibrium, with two kinds of primary factors: import goods and labor. There are two kinds of producers in the domestic economy: retailers and firms. Firms use intermediate domestic and foreign goods, and labor to produce domestic goods. Retailers bundle domestic final goods and foreign final goods with domestic labor. Households consume composite retail goods. Due to the market structures, both domestic goods producers and retailers incorporate a markup into their price. Without loss of generality, trade is balanced. The model is similar to Baqaee and Rubbo (2023) and Silva (2024), except we explicitly add markup and retailers for better mapping with the data.

Households We assume households have homothetic utility of various consumption goods bundled by retailers and indexed by e. This utility, written as $U = U(C_1, ..., C_e, ..., C_E)$, is subject to the budget constraint:

$$\sum_{e=1}^{E} p_e c_e = wL + \sum_{e=1}^{E} \pi_e + \sum_{i=1}^{N} +\pi_i$$

In other words, households earn wages w for their labor L, and retail and domestic-goods producers profits are rebated to households.

Retailers The producers of C_e are monopolistically competitive retailers that combine domestic final goods indexed by i and foreign final goods indexed by i^* with the following Hicks-neutral constant returns to scale production function:

$$x_e = A_e F^e(L_e, \{x_{ei}\}_{i=1,\ldots,N}, \{x_{ei^*}\}_{i^*=1,\ldots,N^*}),$$

where A_e is productivity, L_e is labor, and x_{ei} and x_{ei^*} represent final good quantities used in production.

The cost minimization problem of retailers is

$$\min_{L_e, \{x_{ef}\}_{f=1,\ldots,N}, \{x_{ei^*}\}_{i^*=1,\ldots,N^*}} w_e L_e + \sum_{i=1}^{N} p_i x_{ei} + \sum_{i^*=1}^{N} p_{i^*} x_{ei^*}, \tag{A.1}$$

such that $x_e \geq \bar{x_e}$. Retailers do not use other retailers' goods to generate their aggregate bundle x_e. This means that there is no network structure to track *within* the retailer market.

Each producer e's optimal price in equilibrium is:

$$p_e = (1+\mu_e)MC_e = (1+\mu_e)\frac{TC_e}{x_e} = \frac{(1+\mu_e)}{A_e}\left[\frac{w_e L_e}{x_e} + \sum_{i=1}^{N}\frac{p_i x_{ei}}{x_e} + \sum_{i^*=1}^{N^*}\frac{p_{i^*} x_{ei^*}}{x_e}\right].$$

where μ_e denotes markup, MC_e denotes marginal cost, TC_e denotes total cost, w_e denotes wages, and p_i and p_{i^*} are the prices of x_{ei} and x_{ei^*}, respectively.

To a first order approximation where $d\log y = \hat{y}$, the above expression simplifies to

$$\hat{p}_e = \hat{\mu}_e - \hat{A}_e + (1+\mu_e)\theta_e^L \hat{w}_e + \sum_i (1+\mu_e)\theta_{ei}\hat{p}_i + \sum_{i^*}(1+\mu_e)\theta_{ei^*}\hat{p}_{i^*},$$

where θ_e^L is the sales-based share of factor L defined as $\theta_e^L = \frac{w_e L_e}{p_e x_e}$, $\theta_{ei} = \frac{p_i x_{ei}}{p_e x_e}$ is the sales-based share of domestically produced final good i sold by retailer e, and $\theta_{ei^*} = \frac{p_{i^*} x_{ei^*}}{p_e x_e}$ is the sales-based share of imported good i^* sold by retailer e. Since the above expression holds for each retailer, we can express it in matrix form for all retailers as

$$\hat{P}^E = \hat{M}^E - \hat{A}^E + M^E\left(\Theta^L \hat{W}^E + \Theta\hat{P} + \Theta^*\hat{P}^*\right), \tag{A.2}$$

where $\hat{P}^E$ is a $1 \times E$ vector of all retail price changes, $\hat{M}^E$ and $\hat{A}^E$ are shocks to markups and productivity of retailers, and M^E is a $E \times E$ diagonal matrix of retail markups. The Θ matrices are $E \times N$ sales-based factor shares matrices. $\hat{W}^E$, $\hat{P}$, and $\hat{P}^*$ are wage and producer-price changes. Note that capital letters are either vectors or matrices. If we keep constant all exogenous primitive factor prices and productivity except final goods prices, the above expression collapses to:

$$\hat{P}^E = M^E\left(\Theta\hat{P} + \Theta^*\hat{P}^*\right) \tag{A.3}$$

Domestic Goods The monopolistically competitive producers of the domestic good i's cost minimization function is

$$\min_{L_i, \{x_{ij}\}_{j=1,\ldots,N}, \{x_{ij^*}\}_{j^*=1,\ldots,N}} w_i L_i + \sum_{j=1}^{N} p_j x_{ij} + \sum_{j^*=1}^{N^*} p_{j^*} x_{ij^*}, \tag{A.4}$$

such that $x_i = A_i F^i(L_i, \{x_{ij}\}_{j=1,\ldots,N}, \{x_{ij^*}\}_{j^*=1,\ldots,N}) \geq \bar{x}_i$. Thus, unlike retailers, there is a network structure within domestic good production.

Each producer i optimal price in equilibrium is:

$$p_i = (1+\mu_i)MC_i = (1+\mu_i)\frac{TC_i}{x_i} = \frac{(1+\mu_i)}{A_i}\left[\frac{w_i L_i}{x_i} + \sum_{j=1}^{N}\frac{p_j x_{ij}}{x_i} + \sum_{j^*=1}^{N^*}\frac{p_{j^*} x_{ij^*}}{x_i}\right]$$

As in Baqaee and Rubbo (2023) and Silva (2024), we can show that, to a first order approximation where $d\log y = \hat{y}$ this turns into:

$$\hat{p}_i = \hat{\mu}_i - \hat{A}_i + (1+\mu_i)\frac{w_i L_i}{p_i x_i}\hat{w}_i + \sum_j (1+\mu_i)\frac{p_j x_{ij}}{p_i x_i}\hat{p}_j + \sum_{j^*}(1+\mu_i)\frac{p_{j^*} x_{ij^*}}{p_i x_i}\hat{p}_{j^*}$$

We can express this equation as a function of sales-based factor shares for a factor r, $\Omega^r_{ij} = \frac{p^r_j x^r_{ij}}{p_i x_i}$:[16]

$$\hat{p}_i = \hat{\mu}_i - \hat{A}_i + (1+\mu_i)\Omega^L_i \hat{w}_i + \sum_j (1+\mu_i)\Omega_{ij}\hat{p}_j + \sum_{j^*}(1+\mu_i)\Omega^*_{ij}\hat{p}_{j^*}$$

Since the equation holds for every product i we can express it in matrix form:

$$\hat{P} = \hat{M} - \hat{A} + \Omega^L \hat{W} + M\Omega\hat{P} + M\Omega^*\hat{P}^*,$$

where $\hat{P}$ is the $N \times 1$ vector of domestic price changes, and $\hat{M}$ is the $N \times 1$ vector of markup shocks. Ω^L is the sales-based vector of labor costs, which is a diagonal matrix in this model, though this assumption can be relaxed. Ω is the matrix of intermediate goods cost, while Ω^* is import factor share matrix. M is a diagonal matrix, where each element of the diagonal is the good-specific markup. Inverting the system gives

$$\hat{P} = (\mathbb{I} - M\Omega)^{-1}\left(\hat{M} - \hat{A} + \Omega^L \hat{L} + M\Omega^*\hat{P}^*\right). \tag{A.5}$$

The above equation represents the general case. If we keep constant shocks to productivity, markups, and wages, this collapses to

$$\hat{P} = (\mathbb{I} - M\Omega)^{-1} M\Omega^*\hat{P}^*. \tag{A.6}$$

[16] Alternatively, we can express it in terms of cost-based factor shares $\tilde{\Omega}^r_{ij} = (1+\mu_i)\Omega^r_{ij} = \frac{p_i}{MC_i}\frac{p^r_j x^r_{ij}}{p_i x_i} = \frac{p^r_j x^r_{ij}}{TC_i}$:

$$\hat{p}_i = \hat{\mu}_i - \hat{A}_i + \tilde{\Omega}^L_i \hat{w}_i + \sum_j \tilde{\Omega}_{ij}\hat{p}_j + \sum_{j^*}\tilde{\Omega}^*_{ij}\hat{p}_{j^*}$$

Plugging (A.6) into (A.3), we obtain

$$\hat{P}^E = M^E(\Theta^* + \Theta(\mathbb{I} - M\Omega)^{-1}M\Omega^*)\hat{P}^*. \tag{A.7}$$

If we assume that all markups (retailers and producers) are zero then the matrices M^E and M turn into identity matrices. In this case, the model collapses into one where the value-added component present in observed input-output matrices is another factor of production that we keep constant in dollar terms. Later on, we will call this assumption the "constant-dollar" assumption, as it corresponds to a partial equilibrium scenario where profits remain constant in dollar terms, after a change in foreign prices. We will call the scenario in which markups are constant as in the expression above a "constant-percent" markup assumption, which corresponds to full-passthrough of marginal costs increases.

B Data Mapping Methodology

B.1 Data

We use a number of publicly-available tables from the US Bureau of Economic Analysis (BEA) Input-Output Accounts: the Use Tables, the Make Tables, the Import Matrices, and the PCE bridge.[17] In all cases, we use the "after redefinition" versions of the tables. We define the following matrices corresponding to the data available from the BEA. In doing so, we try to call each matrix with the same nomenclature as BEA (2008) "Mathematical Derivation of the Domestic Requirements Tables for Input-Output Analysis."

- U: The intermediate portion of the total use table, providing the value of each commodity purchased by each industry, in USD million. This is a commodity-by-industry matrix.
- U^*: the intermediate portion of the import matrix, providing the value of each commodity imported by each industry. This is a commodity-by-industry matrix.
- V: the make matrix, providing the value of each commodity made by each industry. This is an industry-by-commodity matrix.
- g: a column vector in which each entry shows the total amount of each industry's gross output
- q: a column vector in which each entry shows the total amount of each commodity's gross output.

[17]The Input-Output Accounts data can be downloaded at the following link: `https://www.bea.gov/industry/input-output-accounts-data`.

- s: a column vector representing total compensation of employees in each industry.
- C: a column vector containing total final demand for each commodity, in producers' prices. This is available in the final demand portion of use matrices.
- C^*: a column vector containing final demand for imports in each commodity, in producers' prices. This is available in the final demand portion of the import matrices.
- R: The PCE concordance matrix between BEA commodity code and BEA NIPA (national income and product account) line, available from the PCE bridge files, evaluated at producers' prices. This is a commodity by expenditure category matrix.[18]
- C^p: a column vector showing personal consumption expenditure in each NIPA category, at purchasers' prices.

We use a few additional publicly-available datasets. First, we use the US Census Bureau Foreign Trade import data, from which we can calculate the total amount imported into the US of each HTSUSA commodity code from each foreign country in each year.[19] Second, we use the BEA-NAICS concordance table, available in the input–output raw data files from the BEA website. Third, we use the aggregated and disaggregated import price indices published by the US Bureau of Labor Statistics (BLS). Finally, we use the seasonally-adjusted average hourly earnings of all employees series from the BLS' Current Employment Statistics (CES) data.

B.2 Mapping the Model to the Data

A key contribution of this paper is to carefully map each model object to its empirical dataset. To emphasize that often what is available in practice does not correspond exactly to what is required by theory we use another notation for empirical objects.

To define the empirical objects, we normalize the data matrices in Section B.1 as follows:

- $B = (U - U^*)\,\mathrm{diag}^{-1}(g)$: domestic direct requirement matrix, showing the domestic inputs required per unit of gross output. It's a N commodities by I industries matrix.
- $B^* = U^*\,\mathrm{diag}^{-1}(g)$: the foreign direct requirement matrix. It's a N commodities by I industries matrix.

[18] The PCE Bridge files can be downloaded at the following link: `https://www.bea.gov/industry/industry-underlying-estimates`.

[19] The Census data can be found at the following link: `https://www.census.gov/foreign-trade/data/dataproducts.html`.

- $D = V\,\text{diag}^{-1}(q)$: market share matrix, showing the proportion of the total output of each commodity produced in each industry. It's an I industries by N commodities matrix.

- $\omega^* = \text{diag}(C^* \oslash C)$: is the share of imported final demand in each commodity, and where $\oslash$ is the Hadamard division operator for element-wise division. It's an N by N matrix.

- $\omega^D = \mathbb{I} - \omega^*$ is the share of domestic goods in final demand. It's an N by N matrix.

- $\tilde{R} = R\,\text{diag}^{-1}(C^p)$: is the bridge matrix normalized by total personal consumption expenditure, representing the share of each commodity's expenditure value in producer prices over expenditure in the retail category at purchaser value. It's an N commodities by E expenditure categories matrix.

There is a now a direct mapping between the matrices in Equation (A.7) and official BEA data. First, note that all theoretical matrices follow the general convention in the literature to have outputs in the row and inputs in the columns of the factor share matrix Ω. The BEA instead specifies inputs in the rows and outputs in the columns of the use tables. Moreover, the BEA distinguishes between commodity and industry in their input-output table. To obtain a commodity-by-commodity input output table we therefore take the input coefficient matrices B and B^* and multiply them by the market share matrix D.

$$
\begin{aligned}
(M\Omega)^\top &= B\tilde{M}D \\
(M\Omega^*)^\top &= B^*\tilde{M}D \\
\text{where} \quad \tilde{M} &= \text{diag}(G \oslash (S + \mathbf{1}^\top U)
\end{aligned}
$$

$\tilde{M}$ is the industry-specific markup over variable cost of the industry, computed as gross output over salaries and cost of materials. Each diagonal element of $\tilde{M}$ can also be written as 1 plus gross operating surplus and taxes over variable costs. Given that we will use this matrix to represent our full pass-through scenario, the above expression effectively assumes that gross-operating surplus and taxes are expressed as a constant percentage on top of variable costs. This assumption can be relaxed with additional data on gross operating surplus decomposition.

Retailers in the model bundle foreign and domestic goods into different retailer categories at once. In the data, the foreign and domestic good share in and the decomposition between purchaser and producer categories come from different sources (use tables vs. bridge files).

Therefore, the matrices Θ and Θ^* can be decomposed into:

$$\begin{aligned} M^E\Theta &= \omega^D \tilde{R}\tilde{M}^E \\ M^E\Theta^* &= \omega^* \tilde{R}\tilde{M}^E \\ \text{where} \quad \tilde{M}^E &= \operatorname{diag}(C^p \oslash (S^E + \mathbf{1}^\top R)) \end{aligned}$$

$\tilde{M}^E$ is the gross markup over variable costs of the retail sector. S^E is a vector of imputed salaries for retail, wholesale and transportation in each expenditure category. It is computed as the share of salaries over cost of materials taken from the use matrix and multiplied by each industry's producer value contribution to personal consumption. Given the above definition the empirical equivalent of equation (A.7) becomes:

$$(\hat{P}^E)^\top = (\hat{P}^*)^\top(\omega^* + B^*\tilde{M}D(\mathbb{I} - B\tilde{M}D)^{-1}\omega^D)\tilde{R}\tilde{M}^E \tag{B.1}$$

B.3 Interpolation of Data from More Detailed Years

BEA input-output tables are published each year. A coarse version of each of the tables is available annually from 1997 to 2023 and includes 71 industry groups and 73 commodity groups. Finer versions with 402 industries and 402 commodities are available in 2007, 2012, and 2017. Similar to the input-output account matrices, the Bridge files also come in two versions: a coarser version with annual updates from 1997 to 2023 using 73 commodity groups and 76 NIPA expenditure groups, and a finer version for 2007, 2012, and 2017 using 402 commodities and 212 NIPA expenditure codes. We use the coarser level of aggregation in the yearly data and multiply the coarse tables by the interpolated cell-blocks share trends from the detailed tables to populate input-output tables at the most disaggregated level for all years between 1997 to 2023.

B.4 Constructing the Consumption-Weighted Import Price Index

As explained, our methodology allows us to compute the import price sensitivity of the NIPA expenditure categories to price changes in BEA commodity categories under two different markup assumptions: constant-percent markup (or full pass-through) and a partial pass-through assumption of constant markups in dollar terms. We can use the BEA-NAICS concordance to group various BEA codes into a single NAICS code. We use NAICS codes that correspond to the most disaggregated NAICS level of the BLS import price series.[20]

[20] For example, the BEA code 1111A0 includes NAICS codes 11111 and 11112, so we map this BEA code to the NAICS code 1111. However, the BLS does not include an import series for NAICS 1111, only 111. Thus, BEA code 1111A0 corresponds to BLS code 111.

If a BEA commodity does not map to a BLS series, we drop that commodity from this analysis, which translates to an assumption of zero import price growth. Because our shares are additive, the rows of the sensitivity matrix Δ that belong to a single NAICS code can simply be added together. The results yields a $P \times E$ matrix, where P refers to the number of these NAICS codes. This matrix $\tilde{\Delta}^{P \times E}$ is akin to the import price sensitivity matrix Δ, except it gives the import price sensitivity of each NIPA category to a change in the price of each NAICS category code. In order to get a $P \times 1$ vector that gives the price sensitivity of core PCE to a change in the price of each NAICS category code, we can do the following operation: $\tilde{\Delta}_{P \times E} J_{E \times 1}$, where J represents a matrix of ones.

In order to turn this sensitivity vector into an index, we reinterpret these sensitivities as shares, and simply rescale these shares so that they sum to one within a date across NAICS codes. We then multiply monthly price changes from the BLS import price series by the shares calculated for that year.