A Matter of Taste: Estimating Import Price Inflation across U.S. Income Groups*

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Abstract

We estimate import price inflation for different income deciles of U.S. consumers over the years 1998 through 2014. After structurally estimating the parameters of a model capturing non-homotheticity across sectors, we use price data from the universe of foreign establishments exporting goods to the U.S. as well as consumer expenditure information to construct import price indexes. We find that lower income households experienced the most import price inflation, while higher income households experienced the least over our time period.

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1 Introduction

How has the cost of living in the United States been affected by changes in import prices over the past two decades? How have these changes been distributed across income groups? These important questions bear directly on current public policy debates over the effects of globalization and international trade on U.S. consumers. Recent research has emphasized the importance of using models in which different income groups can consume goods in different proportions (non-homotheticity), with the consequence that price indexes are income group-specific.

In this paper, we develop a household-level cost of living index based on non-homothetic preferences, and, using detailed trade transaction data from 1998 to 2014, estimate an import price index for different U.S. income deciles. Our structural approach is necessary because it is not possible to build income-group specific import price indexes solely from available U.S. data[1]. To our knowledge, we are the first paper to estimate an import price index by income group for the United States.

Consumer behavior is modeled by a two-tiered nested Constant Elasticity of Substitution demand system. At the upper-tier, non-homotheticity is captured by taste parameters that vary by household, which allow for differences in sectoral expenditure shares across income deciles. At the lower tier, varieties are purchased according to elasticities of substitution that are sector-specific but common across deciles.

We apply the model to trade data containing import prices and consumer survey data containing expenditure shares for different income groups. For prices, we take unit values from the universe of foreign suppliers exporting to the United States from 1998 to 2014, where each of 2.6 million individual foreign supplier-HS10 observations per year is taken as an individual variety. Standard import price indexes typically rely on country-product level observations, so our use of supplier-level trade data means that we have far more precise information about pricing, especially across suppliers within a country. We find that simple averages of the unit values from our data strongly resembles Bureau of Labor Statistics (BLS) averages from survey data on actual quoted import prices, implying that disaggregated unit values are a valid tool to study trends in import prices. We further discipline the model using income-decile expenditure data from the BLS Consumer Expenditure Survey. The expenditure data show that even though the share of total expenditure spent on imports is fairly

[1] Although it is theoretically possible to form income-group specific import price indexes via a group expenditure-share-weighted average of sectoral import prices, Bureau of Labor Statistics sectoral import prices are unavailable for a number of sectors at a high level of disaggregation. Additionally, constructing sectoral import price indexes requires a model, given the lack of data on household level purchases of individual varieties for all imported sectors.

constant across income groups, there are significant differences in the sectoral composition of imported consumption across income groups (i.e., non-homotheticity).

Estimation of the model parameters proceeds in two stages. In the first stage, we estimate the parameters of the lower-tier demand functions using our trade data at the supplier-product level. In the second stage, we estimate the parameters of the upper-tier demand functions at the household level, using both the trade data and the expenditure data.

Before generating import prices using our full model, we first construct a benchmark: a simple Laspeyres price index that corresponds to a first-order approximation of an arbitrary upper-tier demand function. This benchmark shuts down substitution effects by simply weighting sectoral import price indices by (initial period) decile-specific sectoral expenditure shares. Such a first-order approximation approach has been used to study the role of trade in consumption inequalities since Porto (2006), and most recently by Borusyak and Jaravel (2017). For our Laspeyres price index, import prices increased by about 43 percent from 1998 to 2014 for the ninth income decile, or 2.26 percent per year. The first decile experienced import price inflation of about 38 percent from 1998 to 2014, or 2.02 percent per year.

In contrast, our core finding from the fully specified model is that lower income households experienced the most import price inflation, while higher income households experienced the least import price inflation during our time period. For example, in our baseline results the first income decile experienced import price inflation of about 33% from 1998 to 2014, or 1.82 percent per year. For comparison, the ninth income decile only experienced import price inflation of about 21% over that time period, or 1.20 percent per year.

Compared to the Laspeyres benchmark, therefore, we find an upward bias in measured inflation from using a first-order approximation, as would be expected given the absence of sectoral substitution over time. Our main results also demonstrate that such bias is not constant across income deciles in our setting. Indeed, the upward bias for the first income decile is 0.2 percentage points per year, compared to an upward bias of about 0.6 percentage points per year for the median and about 1.1 percentage points per year for the highest income decile. As a result, a standard Laspeyres price index understates differences in import price inflation across deciles.

The result that lower income households faced higher import price inflation is robust to a number of specifications. We find that import prices of non-food, non-energy products exhibit the same patterns as the overall import prices, with the lowest income households facing the highest level of inflation. We also show that Chinese imports held down import price inflation in the U.S. over our time period, but not differentially across income groups. As such, our results suggest that the imported consumption channel may not have mitigated the distributional effects of U.S. trade with China that have occurred through the nominal income channel as documented in Autor et al. (2016), Pierce and Schott (2016), Chetverikov et al. (2016), and the related literature.

Most of the work on constructing import price indexes uses homothetic preferences (e.g., Feenstra (1994), Broda and Weinstein (2006), Khandelwal (2010), Hallak and Schott (2011), Hsieh et al. (2016), Amiti et al. (2017), Feenstra and Weinstein (2017)). Of course, homothetic preferences preclude any focus on distributional issues across consumers[2]. We use non-homothetic preferences, which allow us to study import price inflation across different household income groups.

The economics literature has highlighted two forms of non-homotheticity. First, there is sector-level non-homotheticity (e.g., Neary (2004), Caron et al. (2014), Fajgelbaum and Khandelwal (2016), Cravino and Levchenko (2017)), which reflects differences in sectoral expenditure shares across income groups. Second, there is variety-level non-homotheticity (e.g., Fajgelbaum et al. (2011), Li (2012), Handbury (2013), Feenstra and Romalis (2014)), which the literature has associated with differences in product quality. Although data limitations make studying variety-level non-homotheticity difficult in our context, we exactly match sector-level non-homotheticity from data on sectoral expenditure shares by income decile from the U.S. Consumer Expenditure Survey[3].

Recent papers have used scanner data to study related questions (e.g., Faber (2014), Jaravel (2016), Atkin et al. (2018), Borusyak and Jaravel (2017), Faber and Fally (2017)). However, standard U.S. scanner datasets capture only about 40 percent of goods expenditures in the U.S. Consumer Price Index (Broda and Weinstein (2010)), and do not include most consumer durable products (e.g., cars, cellphones, computers, furniture, apparel). Such datasets also lack country of origin data. In contrast, the trade data we use captures the universe of U.S. goods imports at the supplier level, and allows us to clearly observe the country of origin. To our knowledge, ours is the first paper to estimate import price indexes by income group for the United States.

The most closely related papers to ours are Fajgelbaum and Khandelwal (2016) and Borusyak and Jaravel (2017). Fajgelbaum and Khandelwal (2016) use non-homothetic Almost Ideal Demand and aggregate trade data from many countries to estimate how different income groups in these countries would gain or lose from a counterfactual move to autarky. They find that U.S. consumers in the first decile of income would face a much larger price in-

[2]Recent papers such as Antràs et al. (2017) and Galle et al. (2017) study the distributional effects of trade on the nominal incomes of different types of workers, but in these models workers-as-consumers still have homothetic preferences.

[3]Hottman and Monarch (2018) develop an extended model with additional parametric assumptions in order to capture variety-level non-homotheticity and show how to estimate this model using only aggregate data. Though the model is more detailed, the price index results across households turn out to be similar.

dex increase from moving to autarky than consumers in the ninth decile of income. Borusyak and Jaravel (2017) study how a counterfactual 10% reduction in U.S. trade barriers would affect the wages and consumer price indexes of college graduates and those workers without a college degree, using a log-linear approximation approach. They find that the counterfactual's effect on prices is biased in favor of college graduates, but small enough in magnitude that they conclude that this channel is distributionally neutral. A limitation of this first-order approximation approach is that it omits the effect of gains from product variety, or substitution across either varieties or sectors, on the price indexes of different consumers. Our results show that higher-order effects captured in our full nonlinear approach (specifically substitution effects) are quantitatively important and omitting these effects meaningfully affects measured import price inflation.

In sum, our paper makes three main contributions to the literature. First, our use of supplier-level price data within HS10 products allows us to capture heterogeneity in prices across suppliers within exporting countries. Second, we extend a standard import price estimation methodology to account for non-homotheticity and estimate its parameters. Finally, we document a robust pattern of higher import price inflation for lower-income U.S. households, contributing to our understanding of the distributional consequences of international trade through consumption effects.

The rest of this paper is structured as follows. Section 2 outlines the model. Section 3 describes the data. Section 4 explains our identification strategy and discusses our parameter estimation results. Section 5 presents our import price indexes. Section 6 concludes.

2 Theoretical model

We construct household-specific import price indexes based on a two-tier Constant Elasticity of Substitution framework, where at the upper tier, non-homotheticity is generated from sector-specific taste shifters at the household level, φ_{hst}. Lower-tier varieties are purchased according to a sector-specific elasticity of substitution σ^s.

2.1 Households

We consider a world of many producers, indexed by v. Each v should be thought of as a unique variety, as the data equivalent to any individual variety v will be a supplier-HS10 product pair. The product made by each producer is classified into a broad sector s, which in our empirical application will be an HS4 code.

U.S. consumers have ordinary CES preferences over sectors, such that the utility of household h at time t is given by

$$V_{ht} = \left[\sum_{s \in S} \varphi_{hst}^{\frac{\sigma-1}{\sigma}} Q_{hst}^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}} \tag{1}$$

where V_{ht} is the constant elasticity of substitution aggregate of real consumption of tradable consumer goods sectors for household h at time t, Q_{hst} is the consumption index of sector s for household h at time t, $\varphi_{hst} > 0$ is a taste parameter for sector s for household h at time t, $\sigma > 0$ is an elasticity parameter, and S is the set of tradable consumer goods sectors.

The consumption index of sector s for household h at time t is

$$Q_{hst} = \left[\sum_{v \in G_s} \varphi_{vt}^{\frac{\sigma^s-1}{\sigma^s}} q_{hvt}^{\frac{\sigma^s-1}{\sigma^s}} \right]^{\frac{\sigma^s}{\sigma^s-1}} \tag{2}$$

where q_{hvt} is the real consumption of variety v in sector s for household h at time t, $\varphi_{vt} > 0$ is a demand shifter for variety v at time t[4], $\sigma^s > 0$ is an elasticity parameter for sector s, and G_s is the set of varieties in sector s.

The utility maximizing quantity demanded of variety v in sector s for household h at time t is

$$q_{hvt} = \left(\frac{{p_{vt}}^{-\sigma^s} \varphi_{vt}^{\sigma^s-1}}{P_{st}^{1-\sigma^s}} \right) Y_{hst}, \tag{3}$$

where P_{st} is a sectoral price aggregate given by

$$P_{st} = \left(\sum_{j \in G_s} p_{jt}^{1-\sigma^s} {\varphi_{jt}}^{\sigma^s-1} \right)^{\frac{1}{1-\sigma^s}}, \tag{4}$$

Y_{hst} is the expenditure on sector s for household h at time t, and p_{vt} is the variety-specific price at time t.

The utility maximizing expenditures of household h on sector s is:

$$Y_{hst} = \frac{\varphi_{hst}^{\sigma-1} {P_{st}}^{1-\sigma}}{\sum_{r \in S} \varphi_{hrt}^{\sigma-1} {P_{rt}}^{1-\sigma}} Y_{ht}, \tag{5}$$

where Y_{ht} is the total expenditure of household h at time t, S is the number of sectors, and P_{st} is the sectoral price aggregate. This equation shows that these preferences feature

[4]If we had household-level data on variety purchases, we could allow the taste shifter for variety v to vary across households (φ_{hvt}).

non-homotheticity at the sector-level, because we allow the sector-level taste shifters (φ_{hst}) to be different across income groups.

We have the following price index for household imported consumption:

$$P_{ht} \equiv \left(\sum_{s \in S} \varphi_{hst}^{\sigma-1} {P_{st}}^{1-\sigma} \right)^{\frac{1}{1-\sigma}}, \tag{6}$$

so that the change in the import price index for household h from time t to time $t+i$ (i.e., import price inflation) can be written as:

$$\frac{P_{ht+i}}{P_{ht}} = \frac{\left(\sum_{s \in S} \varphi_{hst+i}^{\sigma-1} {P_{st+i}}^{1-\sigma} \right)^{\frac{1}{1-\sigma}}}{\left(\sum_{s \in S} \varphi_{hst}^{\sigma-1} {P_{st}}^{1-\sigma} \right)^{\frac{1}{1-\sigma}}}. \tag{7}$$

2.2 Firms

We close the model by describing firm behavior. We assume that firms producing variety v in each sector engage in monopolistic competition and take the sector price index and sector expenditure as given[5].

Market demand for variety v in sector s at time t (given by $q_{vt} = \sum_h q_{hvt}$) can be written as

$$q_{vt} = \left(\frac{{p_{vt}}^{-\sigma^s} \varphi_{vt}^{\sigma^s-1}}{{P_{st}}^{1-\sigma^s}} \right) Y_{st}, \tag{8}$$

where Y_{st} is aggregate U.S. expenditure on imports in sector s.

Given our demand structure, firms will set a constant markup on each variety they sell:

$$p_{vt} = \frac{\sigma^s}{\sigma^s - 1} c_{vt} \tag{9}$$

where c_{vt} is the marginal cost of variety v at time t.

In specifying the firm's cost structure, we allow marginal costs c_{vt} to be variable, (weakly) increasing in output, and given by

$$c_{vt} = \delta_{vt}(1+\omega^s) q_{vt}^{\omega^s} \tag{10}$$

where $\omega^s \geq 0$ parameterizes the convexity of the cost function in sector s and $\delta_{vt} > 0$ is a variety-level shifter of the cost function.

[5]Technically, firms do not internalize their effect on the sector price index because they are assumed to be measure zero with regard to the market in which they operate.

We lay out in Section 4 a tractable approach along the lines of Feenstra (1994) to estimate the underlying demand parameters φ_{hst} and σ^s, but first describe the data used to discipline the model.

3 Data

In order to construct household-level import price indices, there are two main data requirements in our framework: prices, p_{vt} where v is a variety in sector s, and household-level expenditure on sector s, Y_{hst}[6]. A third data requirement for estimating parameters such as φ_{vt} and σ^s is sales of variety v, $p_{vt}q_{vt}$. Section 3.1 describes how we use U.S. import data to generate p_{vt} and $p_{vt}q_{vt}$ while Section 3.2 describes how we use the U.S. Consumer Expenditure Survey to generate Y_{hst}.

3.1 Trade Data

For the empirical implementation, we will define a variety to be the combination of a foreign firm exporting to the United States and an HS10 product code. Prices and sales at the variety level are thus much more disaggregated than is typically found in the literature, where a variety is the combination of an exporting country and an HS10 product code. The richness of the data allows us to account for heterogeneity in prices among suppliers from the same country.

The international trade data come from the Linked-Longitudinal Firm Trade Transaction Database (LFTTD), which is collected by U.S. Customs and Border Protection and maintained by the U.S. Census Bureau. Every transaction in which a U.S. company imports a product requires the filing of Form 7501 with U.S. Customs and Border Protection, and the LFTTD contains the information from each of these forms[7]. There are typically close to 40 million transactions per year.

We use the import data from 1998 to 2014, which includes the quantity and value exchanged for each transaction, Harmonized System (HS) 10 product classification, date of import and export, country of origin, and a code identifying the foreign supplier. Sales of an variety are simply the imported value associated with that variety, while prices are constructed as unit values, dividing variety-level value by quantity. These unit values are thus

[6]Note that household-level purchases on the universe of individual imported varieties is not currently available data.

[7]Approximately 80 to 85 percent of these customs forms are filled out electronically (Kamal and Krizan (2012)).

in the units of dollars per quantity. In the LFTTD, physical quantity units are specific to HS10 products[8].

The foreign supplier identifier, known as the *manufacturing ID*, or *MID*, contains limited information on the name, address, and city of the foreign supplier[9]. Monarch (2016) and Kamal and Monarch (2018) find substantial support for the use of the MID as a reliable, unique identifier, both over time and in the cross section. Pierce and Schott (2012), Kamal and Sundaram (2016), Eaton et al. (2014), Heise (2015), and Redding and Weinstein (2017) have all used this supplier identifier, and Redding and Weinstein (2017) also show that many of the salient features associated with exporting activity (such as the prevalence of multi-product firms and high rates of product and firm turnover) are replicated for MID-identified suppliers.

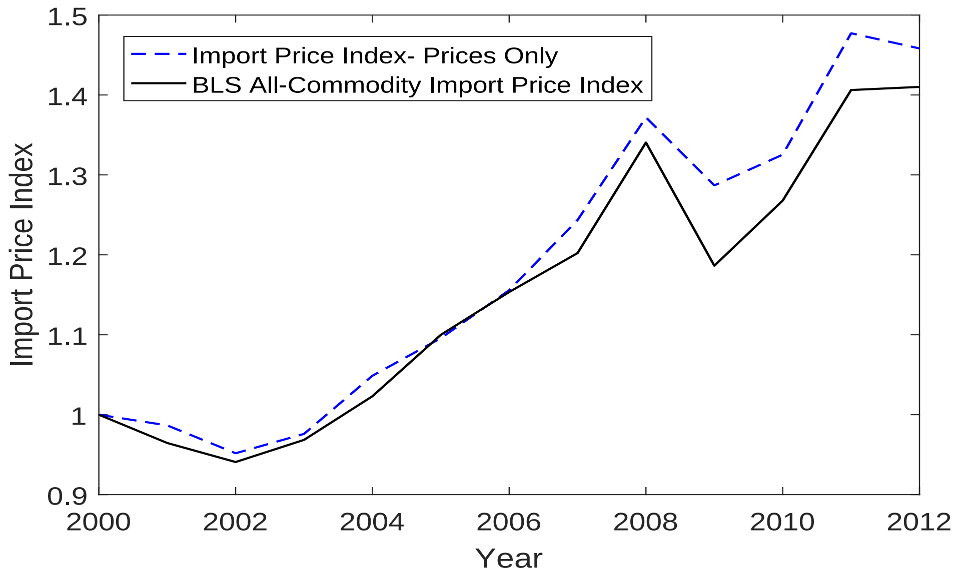
We build on the methods of Bernard et al. (2009) for cleaning the LFTTD. Specifically, we drop all transactions with imputed quantities or values (which are typically very low-value transactions) or converted quantities or values. We also drop all observations without a valid U.S. firm identifier. After making these reductions, the average year has close to 2.6 million imported varieties (supplier-HS10 pairs).

We can use the LFTTD data to generate a model-free import price index by taking the geometric average of variety-level unit values in each sector, then taking the geometric average across sectors. A useful comparison for this object is the BLS All-Commodity Import Price Index, which is a Laspeyres price index constructed from survey data gathered through the International Price Program. We illustrate these two series in Figure 1. The two import prices indexes are remarkably similar, even though the data sources are markedly different. We treat this finding as evidence that our unit value source data is suitable for constructing import price indexes.

[8]The most common quantity unit is weight in kilograms.

[9]Specifically, the MID contains the first three letters of the producer's city, six characters taken from the producer's name, up to four numeric characters taken from its address, and the ISO2 code for the country of origin.

Figure 1: U.S. Import Price Indexes, 2000-2012



3.2 Consumer Expenditure Data

This subsection outlines the construction of the expenditure on imports of sector s by household h, Y_{hst}, a key input for estimating the parameters of the model. We use the overall sectoral expenditure by a representative household in different income deciles, and transform this to imported expenditure by using sector-specific import penetration shares. Information on household expenditure comes from the BLS Consumer Expenditure Survey (CE) public data, which provides information on how 10 income deciles allocate their expenditure across different CE categories. The CE is the data that underlie the category expenditure weights in the U.S. Consumer Price Index.

One complication from using the CE is that the dollar value of expenditure across categories by income deciles is only available directly in 2014 (prior years only report expenditure by quintiles)[10]. We therefore apply 2014 expenditure shares to total expenditure by decile in each year going back to 1998 beginning in 2014.

In order to use this decile expenditure information across all years and for all imported categories, we undertake the following steps:

1. The CE provides data on total expenditure by various income levels (by bands of 10,000 dollars, until incomes of 70,000 dollars and above) by year. Apply the appropriate

[10]The public-use microdata for earlier years has income top-coding above the 6th decile, so we cannot use this data to calculate decile-level expenditure shares for earlier years. In principle, we could use the non-public microdata to produce decile-level tables prior to 2014.

expenditure-to-income ratios to Census data on the dollar income levels of each decile to obtain total expenditure in every year for every income decile[11].

2. Apply the 2014 decile-specific expenditure shares across CE categories to each year's decile total expenditure to get decile-specific expenditure on each CE category.

3. Concord the CE categories to HS4 codes to get decile-specific expenditure on each HS4 category.

4. Apply the import share in domestic absorption for each year to create decile-specific imported expenditure in each HS4 category.

For Step 1, we construct expenditure-to-income ratios using the appropriate group from the CE. We then generate total expenditures by applying these ratios to Census estimates of income decile. For example, the first income decile had an income of $14,070 in 1998, and the CE for 1998 indicates that people who earned between $10,000 and $15,000 had expenditures equal to 1.613 of their income, on average, so we impute total expenditure for a household in that decile in 1998 to be $22,691.64. The implied expenditure numbers appear reasonably free from large year-to-year swings. After this, we apply the decile-specific category expenditure shares from 2014 to each of these implied total decile expenditure numbers (Step 2). This is a workaround to the fact that the BLS only provides decile-specific total expenditure and category expenditure shares for 2014. When we look at earlier years, we find that the category expenditure shares by quintile do not change significantly from 1998 to 2013[12].

For Step 3, we use a concordance between the categories in the CE and Harmonized System categories developed by Furman et al. (2017)[13]. An important fact to note here is that only about 20% of HS4 sectors can be found in consumer expenditures, while the rest are intermediate inputs. In the end, we will use about 250 HS4 sectors in the household price indexes. Although this is only a subset of all imported goods, we find that about 55% of total U.S. goods import value is in HS4 categories that can be concorded to the CE. Additionally, 361 of the 787 total expenditure categories in the CE can be linked to an imported HS4

[11]For the eighth and ninth deciles, where incomes well exceed 70,000 dollars, we instead applied the observed 2014 expenditure-to-income ratio to their income in all other years. Note that the year-to-year variation in these ratios for the other deciles is relatively small, especially at higher incomes.

[12]For example, using the expenditure shares of the broad CE categories (Food, Housing, Apparel, Transportation, Healthcare, and Entertainment) we find a correlation between the 1998 quintile shares and the 2013 quintile shares of 0.99.

[13]In cases where one CE category maps into multiple HS4 categories, we use the share of total U.S. import expenditure to allocate spending across HS4s.

category, while the remainder are mainly services[14].

Step 4 entails converting total HS4 expenditure into imported HS4 expenditure. To do this, we multiply by the sectoral import share in domestic absorption for each year, which is defined as in Feenstra and Weinstein (2017). Household-specific expenditure on imports from sector s are given by

$$Y_{hst} = E_{hst}\left(\frac{M_{s,t}}{G_{s,t} - X_{s,t} + M_{s,t}}\right), \tag{11}$$

where E_{hst} is the sector-level expenditure by household h derived in Steps 1-3, $M_{s,t}$ is the nominal value of U.S. imports in sector s; $G_{s,t}$ is the nominal value of U.S. production in sector s; and $X_{s,t}$ is the nominal value of U.S. exports in sector s. We use total sectoral output data from the BEA to construct $G_{s,t}$, and aggregate imports and exports from the LFTTD to construct $M_{s,t}$ and $X_{s,t}$[15]. Also, to clarify notation, summing Y_{hst} across sectors will result in total expenditure on imports, not total expenditure in the CE. Note that although $\frac{E_{hst}}{\sum_s Ehst}$ will be constant over time by construction (since we only have CE decile shares for 2014), sector s's share of household h's import basket ($\frac{Y_{hst}}{\sum_s Y_{hst}}$) will not be constant over time because sectoral import shares in domestic absorption have different sectoral trends. Specifically, when we compute the percent change between 1998 and 2014 for each sector's share of each decile's imported consumption ($\frac{Y_{hst}}{\sum_s Y_{hst}}$), we find that, across all decile-sectors, the 25th percentile decile-sector has a 27.6% decrease in share, the median has a 7.1% increase in share, and the 75th percentile has an 85.8% increase in share.

We find several interesting facts from our Y_{hst} calculation[16]. First, the share of imports in total expenditure does not differ much across income groups: we find that in 2014, the share of imports in actual expenditure averaged about 10% across deciles, with a standard deviation of 0.5 percentage points. Thus, any differences in import price indexes across income groups can be meaningfully compared because there are small differences in shares of imports in consumption. Table 1 shows the share of total expenditure on imports across

[14] Although it is theoretically possible to measure the extent to which imported intermediate inputs affect the consumer categories in the CE and thus import penetration and Y_{hst}, we chose not to rely on additional concordances from input-output tables for calculating our results.

[15] $G_{s,t}$ is constructed using a concordance between NAICS codes and HS codes. In cases where one NAICS code maps into multiple HS4 categories, we use the share of U.S. exports in each sector to allocate production across HS4s.

[16] Since we are unable to disclose the whole set of Y_{hst} from the restricted data setting, these summary statistics use a version of Y_{hst} constructed from publicly available trade data, which is aggregated from the LFTTD. The only possible difference between these two versions would be the inclusion of a few sectors that lacked enough observations for our estimation procedure, and is very unlikely to have different overall implications.

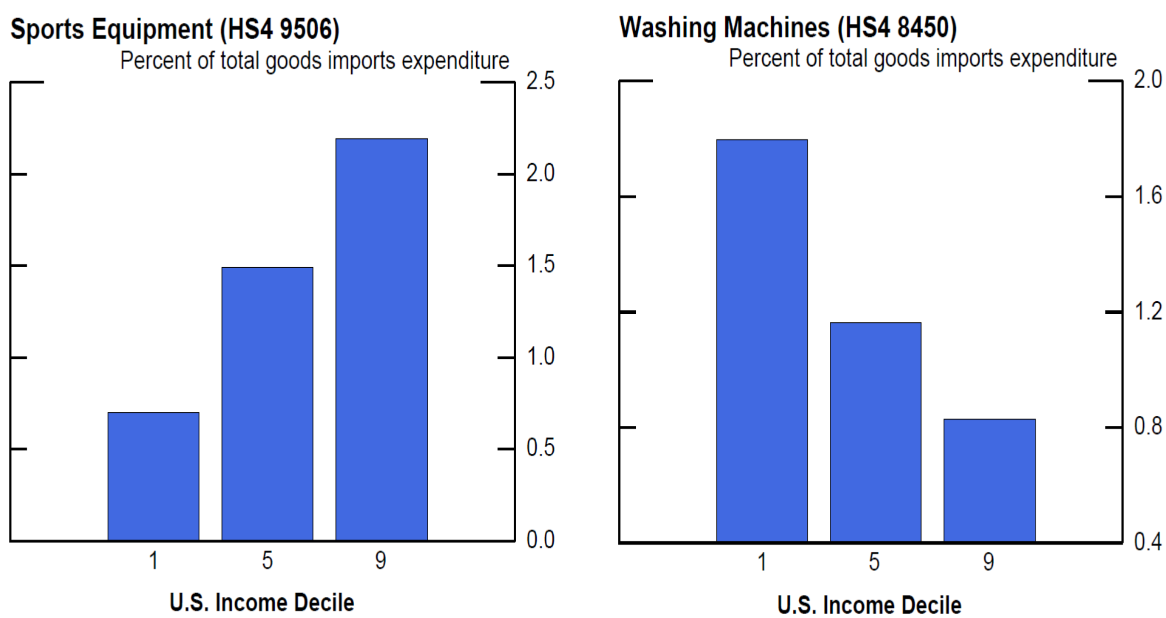
different deciles in 1998 and 2014. Interestingly, there is not much variation across deciles in the cross section, but the share of spending on imports does increase over our time period.

Table 1: Share of Expenditure on Imports by U.S. Decile of Income, 1998 and 2014 (%)

Year	1st Decile	2nd Decile	4th Decile	5th Decile	6th Decile	8th Decile	9th Decile
1998	6.49	6.58	6.35	6.99	7.49	7.01	7.05
2014	9.96	9.22	9.24	10.05	10.63	10.02	10.06

Second, non-homotheticity across imported sectors is evident from the data. For each household, we create the ratio of expenditure on an imported category as a share of total expenditure on imports: $Y_{hst}/\sum_s Y_{hst} \equiv Y_{hst}/Y_{ht}$. Even just from summarizing this object, it is clear that there are notable differences within sectors. Figure 2 shows two examples: spending on imported washing machines and sports equipment in 2014 differ noticably by income decile.

Figure 2: Selected Categories as a Share of Imported Consumption, by Income Decile



A more comprehensive way to show sectoral non-homotheticity is to compare the distribution of expenditure shares (again, $\frac{Y_{hst}}{\sum_s Y_{hst}} \equiv \frac{Y_{hst}}{Y_{ht}}$) across income deciles. Table 2 presents summary statistics across HS4 categories, weighted by expenditure in an HS4. We find meaningful variation across deciles. Panel (a) of Table 2 presents summary statistics for the ratio of Decile 9 expenditure shares over Decile 1 expenditure shares in 2014 ($\frac{Y_{9st}/Y_{9t}}{Y_{1st}/Y_{1t}}$). The 25th and 75th percentiles demonstrate a wide range of differences in expenditure shares across these deciles. Panels (b)-(d) show similar findings for other decile comparisons in 2014.

Table 2: Summary Statistics for Decile-to-Decile Expenditure Share Ratios in 2014

(a) Decile 9 to Decile 1 $\left(\frac{Y_{9st}/Y_{9t}}{Y_{1st}/Y_{1t}}\right)$

10th Percentile	25th Percentile	Median	75th Percentile	90th Percentile
0.6101	0.7313	1.0068	1.1271	1.7832

(b) Decile 9 to Decile 5 $\left(\frac{Y_{9st}/Y_{9t}}{Y_{5st}/Y_{5t}}\right)$

10th Percentile	25th Percentile	Median	75th Percentile	90th Percentile
0.7370	0.8644	0.8918	1.1753	1.4986

(c) Decile 2 to Decile 5 $\left(\frac{Y_{2st}/Y_{2t}}{Y_{5st}/Y_{5t}}\right)$

10th Percentile	25th Percentile	Median	75th Percentile	90th Percentile
0.2735	0.9220	1.1292	1.3089	1.4230

(d) Decile 2 to Decile 1 $\left(\frac{Y_{2st}/Y_{2t}}{Y_{1st}/Y_{1t}}\right)$

10th Percentile	25th Percentile	Median	75th Percentile	90th Percentile
0.6228	0.9254	1.0806	1.1438	1.3301

4 Estimation

In this section, we describe our strategy for recovering the parameters of the model laid out in Section 2, using the data described in Section 3 as inputs. Importantly, we can estimate the parameters of the partial equilibrium model without relying on assumptions about the distribution of firm productivity, the nature of production functions, or a full general equilibrium framework.

Our estimation will proceed in two stages. In the first stage, we will estimate the parameters of the lower-tier demand functions using our trade data at the supplier-product level. To address endogeneity concerns, we apply the Feenstra (1994) approach of identification via heteroskedasticity to estimate the model.

In the second stage, we will estimate the parameters of the upper-tier demand functions at the household level, using both the trade data and the expenditure data. To deal with possible endogeneity, we develop an instrumental variables strategy for this setting. These two stages of estimation will recover all of the parameters of our model, which, when combined with the microdata, allow us to construct household-level import price indexes.

4.1 Estimating Variety-level Demand

For each sector s, the deep parameters to be estimated are σ^s and ω^s. Conditional on estimating these parameters, the variety-level unobservables of φ_{vt} (demand shifters), δ_{vt} (cost shifters), and c_{vt} (marginal costs) can be recovered from the model's structure given the data on prices and sales.

To estimate these parameters, we apply the Feenstra (1994) approach of identification via heteroskedasticity to our framework. Identification via heteroskedasticity has also been utilized in other recent papers (Rigobon (2003), Lewbel (2012)).

Start from the variety-level demand expression in Equation 8. Taking logs, taking the time difference and differencing relative to another variety k in the same sector s gives

$$\Delta^{k,t}\ln(p_{vt}q_{vt}) = (1-\sigma^s)\Delta^{k,t}\ln(p_{vt}) + \upsilon_{vt}, \tag{12}$$

where $\Delta^{k,t}$ refers to the double difference. The unobserved error term is $\nu_{vt} = (1-\sigma^s)\left[\triangle^t \ln\varphi_{kt} - \triangle^t \ln\varphi_{vt}\right]$, where $\triangle^t$ refers to a single difference across time periods.

Next, we work with the variety-level pricing expression in Equation 9. Multiplying both sides by $p_{vt}^{\omega_s}$, taking logs, re-arranging, and double-differencing as before gives

$$\Delta^{k,t}\ln p_{vt} = \frac{\omega^s}{1+\omega^s}\Delta^{k,t}\ln(p_{vt}q_{vt}) + \kappa_{vt}, \tag{13}$$

where the unobserved error term is $\kappa_{vt} = \frac{1}{1+\omega^s}\left[\triangle^t \ln\delta_{vt} - \triangle^t \ln\delta_{kt}\right]$.

As in Feenstra (1994), we assume that the following orthogonality condition holds for each variety:

$$G(\beta_s) = \mathbb{E}_{\mathbb{T}}\left[x_{vt}(\beta_s)\right] = 0 \tag{14}$$

where $\mathbb{E}_{\mathbb{T}}$ is the time series expectation, $x_{vt} = \nu_{vt}\kappa_{vt}$, and $\beta_s = \begin{pmatrix} \sigma^s \\ \omega^s \end{pmatrix}$.

In words, we are assuming the orthogonality of the idiosyncratic demand (ν_{vt}) and supply (κ_{vt}) shocks at the variety level, after variety and sector-time fixed effects have been differenced out. As in Feenstra (1994), the supply shock κ_{vt} is the residual of the pricing equation after accounting for fixed effects and the variation in prices due to movements along upward-sloping supply curves. The supply shock κ_{vt} thus represents shifts over time in the intercept of the variety-level supply curve- changes in price over time that occur for reasons other than changes in quantity sold. Our assumption is that these intercept shifts are uncorrelated with shifts over time in the intercept of the variety-level demand curve. This orthogonality assumption is arguably more plausible in our setting than in prior research because we are using supplier-product trade data. A remaining concern could be quality upgrading, which might simultaneously shift both the demand and pricing equations. To address this possible concern, we consider in a robustness check below how our parameter estimates change when we use only a sample of multi-variety firms, which allows us to difference out firm-sector-time fixed effects from the supply and demand error terms.

The objective function is formed for each sector s by stacking the orthogonality conditions, so that the GMM problem is:

$$\hat{\beta}_s = \arg\min_{\beta_s} \{G^*(\beta_s)' W G^*(\beta_s)\} \tag{15}$$

where $G^*(\beta_s)$ is the sample counterpart of $G(\beta_s)$ stacked over all varieties in sector s and W is a positive definite weighting matrix[17]. Following Broda and Weinstein (2006), we give more weight to varieties that are present in the data for longer time periods and sell larger quantities[18].

After obtaining ω^s and σ^s for each sector, we can recover the variety-level demand shifters. Although most papers in the literature on price index construction impose the assumption that variety-level quality is fixed over time, Redding and Weinstein (2016) show that the price index is still well-behaved so long as variety-level quality is unchanged on average. Therefore, in this spirit, we normalize the geometric average of demand shifters in each sector to be one for all time periods (i.e., $\widetilde{\varphi_{kt}} = \widetilde{\varphi_k} = 1$ across varieties in each sector, where the tilde denotes the geometric average). Then, the demand shifter for each variety can be computed differencing Equation 8 relative to the geometric average to get the following expression

$$\varphi_{vt} = \exp\left[\frac{\ln(p_{vt}q_{vt}) - \ln(\widetilde{p_{kt}q_{kt}}) + (\sigma^s - 1)(\ln p_{vt} - \ln \widetilde{p_{kt}})}{\sigma^s - 1}\right], \tag{16}$$

where $(\widetilde{p_{kt}q_{kt}})$ is the geometric average of $(p_{kt}q_{kt})$ across varieties in the sector at time t[19]. Importantly, the variety-specific taste parameters scale in units of prices, thereby allowing comparison of prices across varieties.

[17]In principle, one could use the optimal GMM weighting matrix, but optimal GMM is known to have a serious small-sample bias in a setting like ours.

[18]Varieties with larger import volumes are expected to have less measurement error in their unit values.

[19]The other remaining model parameters, c_{vt} (marginal costs), and δ_{vt} (cost shifters) are straightforward to compute from Equations 9, and 10, respectively.

4.2 Estimating Sector-level Demand

With the previously estimated parameters as well as our constructed expenditure on imports by HS4 sector s, Y_{hst}, it is possible to estimate the overall elasticity of substitution σ. Starting from the household sector-level demand expression in Equation 5, take the time difference and difference relative to another sector k bought by the same household h. This double-differencing gives

$$\Delta^{k,t}\ln(Y_{hst}) = (1-\sigma)\Delta^{k,t}\ln(P_{st}) + \upsilon_{hst}, \tag{17}$$

where $\upsilon_{hst} = (\sigma - 1)\left[\Delta^{k,t}\ln\varphi_{hst}\right]$. We can construct the objects that enter this equation using our previous parameters and the data. We then form our estimating equation by pooling the double-differenced observations across households, sectors, and time. Note also that this equation depends only on relative log-changes, such that time-invariant differences across sectors do not affect this equation.

We expect that running Ordinary Least Squares on the above equation would not produce a consistent estimate of σ, because of potential endogeneity bias from a possible correlation between the sectoral price index and the error term. To address this potential issue, we pursue an instrumental variables approach as in Hottman et al. (2016). They note that the change in the log of the sectoral price index can be linearly decomposed into four terms as follows:

$$\begin{aligned}\Delta^{k,t}\ln P_{st} = {} & \Delta^{k,t}\left(\frac{1}{N^v_{st}}\sum_{v\in G_{st}}\ln p_{vt}\right) - \Delta^{k,t}\left(\frac{1}{N^v_{st}}\sum_{v\in G_{st}}\ln\varphi_{vt}\right) \\ & -\Delta^{k,t}\frac{1}{\sigma^S-1}\ln N^v_{st} - \Delta^{k,t}\frac{1}{\sigma^S-1}\ln\Big(\frac{1}{N^v_{st}}\sum_{v\in G_{st}}\frac{\left(\frac{p_{vt}}{\varphi_{vt}}\right)^{1-\sigma^S}}{\widetilde{\left(\frac{p_{vt}}{\varphi_{vt}}\right)^{1-\sigma^S}}}\Big),\end{aligned} \tag{18}$$

where N^v_{st} is the number of varieties in sector s at time t. We use the fourth term on the right-hand side, which measures the change in dispersion in quality-adjusted variety-level prices within a sector, as an instrument for the change in the price index term when we estimate Equation 17. We use this term because the first and third terms on the right-hand side are likely correlated with changes in the sector-level demand shifter, as average prices rise and varieties enter in response to positive sector demand shocks. Our identifying assumption for the instrumental variables regression is that the changes in dispersion in quality-adjusted prices within a sector are uncorrelated with the changes in the sector-level demand shifter φ_{hst}. Based on that assumption, we estimate Equation 17 using two-stage least squares to obtain an estimate of σ.

Given an estimate of σ, we can then solve for the household-specific sectoral demand shifters (φ_{hst}). Along the lines of the above calculation of φ_{vt}, this can be done by normalizing $\widetilde{\varphi_{hkt}} = \widetilde{\varphi_{hk}} = 1$ across sectors and using Equation 5 in differences to derive

$$\varphi_{hst} = \exp\left[\frac{\ln(Y_{hst}) - \ln(\widetilde{Y_{hkt}}) + (\sigma - 1)(\ln P_{st} - \ln \widetilde{P_{kt}})}{(\sigma - 1)}\right] \tag{19}$$

Therefore, the sectoral level demand shifters are a function of household expenditure on imports in that sector and the accompanying sectoral price index, relative to that household's geometric average across sectors. These taste parameters φ_{hst} are the key determinant of non-homotheticity in the model and drive the differences in import prices between groups.

4.3 Implementation

The first estimation stage entails estimating Equation 15 using the trade data. To conduct the parameter estimation, we use only those varieties that are present for six or more years in our data. Furthermore, as Equation 15 relies on double-differenced price and sales terms as components, we winsorize by dropping double-differenced variety price and sales changes that are below the 1st percentile and above the 99th percentile[20]. Importantly, these are changes we make only to the parameter estimation sample; the import price results use the complete set of variety-level data[21].

We run our estimation routine on each HS4 sector where there are enough observations to do so, which amounts to 980 HS4 sectors and over 95% of total U.S. goods imports[22]. Even though many of these sectors are not household-facing, we perform the estimation for all possible imported sectors in order to compare with alternative parameter estimates from other work. The parameters are estimated using a nonlinear solver to solve the GMM problem described in Equation 15 for sectors. We directly impose constraints on this nonlinear estimation[23]. Our approach contrasts with the two-step process of Broda and Weinstein (2006) and the related literature, which involves estimating parameters from the unconstrained GMM problem in the first step and then conducting a grid search when the parameters from the unconstrained estimation take implausible values. After obtaining estimates of σ^s, ω^s, and φ_{vt}, we then generate the sectoral price indices P_{st} using Equation 4.

[20] These data cleaning procedures, along with the weighting matrix used in our GMM estimation, help address the small-sample, outlier-overweighting bias discussed in Soderbery (2015).

[21] The decile-specific import price indexes use data from about 250 consumer-facing HS4 sectors.

[22] We define sectors in our estimation at the HS4 level in order to balance the number of observations available for estimation with the level of disaggregation. We drop any HS4 sector that features fewer than 30 varieties over our 17 years of data.

[23] We impose the following constraints: $\sigma^s \geq 1.01$ and $\omega^s \geq 0$.

The second estimation step is the estimation of the sectoral demand equations at the household level. Here, we work with household sectoral expenditure Y_{hst}, constructed as in Section 3.2, and P_{st}. We estimate Equation 17 to obtain σ. Constructing the household-level taste shifters as in Equation 19 means that all the ingredients needed to generate household-specific import price indexes from Equation 7 are available.

4.4 Parameter Estimates

First, we report our estimates of σ^s in Table 3, which are the sectoral-level elasticities of substitution across varieties. In all sectors, our estimate of σ^s is statistically different from zero at least at the 5 percent level. Across sectors, our estimates of the elasticity of substitution have a median of 4.4, squarely in line with earlier findings for U.S. imports[24].

Table 3: Summary of σ^s

10%	Median	90%
2.82	4.44	8.42

Another parameter that corresponds with earlier work is the elasticity of marginal cost with respect to output, ω_s. In all but a handful of sectors our estimate of ω_s is also statistically different from zero at the 5 percent level. Again, our estimated parameters are in line with previous work[25].

Table 4: Summary of ω_s

10%	Median	90%
0.16	0.40	1.46

Table 5 reports our estimate of σ, which is the aggregate elasticity of substitution (across consumer goods). The first column shows the OLS result from our estimating equation, while the second column reports the Instrumental Variable (IV) estimate. As would be expected

[24] For comparison, starting with the Broda and Weinstein (2006) estimates of σ^s at the HS10 level for U.S. imports from 1990-2001, and collapsing to the HS4 level by taking the mean across HS10 estimates, then the 10th percentile value of σ^s is 1.91, the median is 4.46, and the 90th percentile is 22.5.

[25] For comparison, Soderbery (2015) reports hybrid Feenstra estimates of ω_s for U.S. imports at the HS8 level from 1993 to 2007, which range from 0.03 at the 25th percentile to 1.06 at the 75th percentile, with a median of 0.26. After collapsing to the HS4 level by taking the median of ω_s across these HS8 estimates, then the 10th percentile value of ω_s is 0.03, the median is 0.30, and the 90th percentile is 14.09.

from the presence of an endogeneity bias in this setting, the OLS estimate is biased toward zero. The IV estimate of σ is about 2.3, with a 95 percent confidence interval between 2.2 and 2.4. Note that many papers in the trade and macroeconomics literature assume that $\sigma = 1$, making upper-tier utility Cobb-Douglas. Redding and Weinstein (2017) also estimates the elasticity of substitution across U.S. HS4 import sectors from 1997-2011, and reports an estimate of 1.36.

Table 5: Estimates of σ

OLS estimate	IV estimate	IV 95% C.I.
0.71	2.30	(2.15 - 2.44)

Before moving on to discuss the household price indices implied by these parameters, we circle back to discuss the exclusion restriction at the heart of our Feenstra (1994) style estimation approach. Recall the identifying assumption that the idiosyncratic demand shocks (changes in φ_{vt}) and supply shocks (changes in δ_{vt}) at the variety level are assumed to be orthogonal after variety and sector-time fixed effects have been differenced out. To further remove firm-sector-time fixed effects from the supply and demand shocks, we re-estimate our parameters using only a sample of suppliers exporting multiple products within a sector as a robustness check. The estimation sample drops significantly, because the only identifying variation within a sector now comes from double-differencing varieties within the same supplier. Nonetheless, we find parameter values that are quite similar to the baseline. Thus, our estimates are robust to this more exacting specification.

5 Household-Level Import Price Inflation

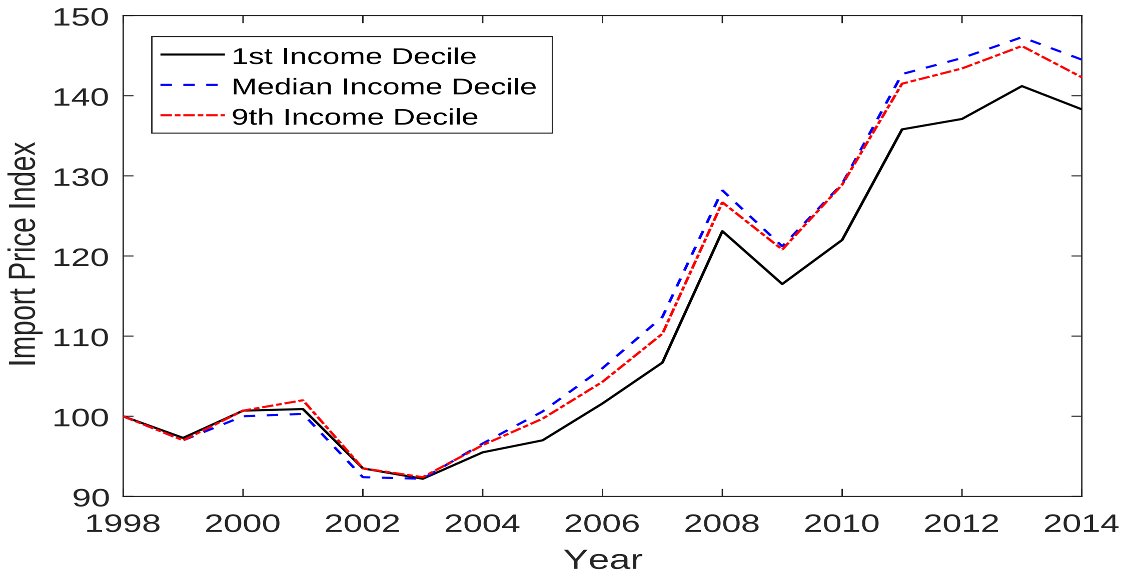
Next, we use our parameter estimates to construct measures of import price inflation by income decile.

5.1 Laspeyres Benchmark

Before we present our full, nonlinear price indexes that account for substitution patterns and movements in taste shifters over time, we first present decile-specifc Laspeyres price indexes, constructed by taking a weighted average of the sector-level price indices P_{st}. The weights used are 1998 import expenditure shares on HS4 products by decile. These Laspeyres indexes can be rationalized as the result of a first-order approximation to an arbitrary upper-tier demand system. The results of this exercise are shown in Figure 3.

Figure 3 reports import price indexes for selected income deciles over the entirety of 1998 through 2014, namely the first, median, and ninth deciles of income in the United States. The figure shows that for the ninth decile, import prices increased by about 43 percent from 1998 to 2014, or 2.26 percent per year. In contrast, the first decile experienced cumulative import price inflation of about 38 percent from 1998 to 2014, or 2.02 percent per year.

Figure 3: U.S. Import Price Index, Laspeyres Benchmark



5.2 Import Price Indexes from Full Model

Figure 4 reports the results for our fully specified price indexes. The dotted lines in the figure represent error bands, computed by recalculating the income-decile specific price indexes using values of σ that represent the 95% confidence interval thresholds for this parameter.

There are several notable features of Figure 4. In particular, note that the price index for the ninth decile of income is below the other deciles shown in every year after 2002. The ninth income decile only experienced import price inflation of about 21% over that time period, or 1.20 percent per year. By comparison, the first income decile experienced import price inflation of about 33% from 1998 to 2014, or 1.82 percent per year. The set of import price index values for all deciles for selected years are given in Table 6.

Figure 4: U.S. Import Price Index, Full Model

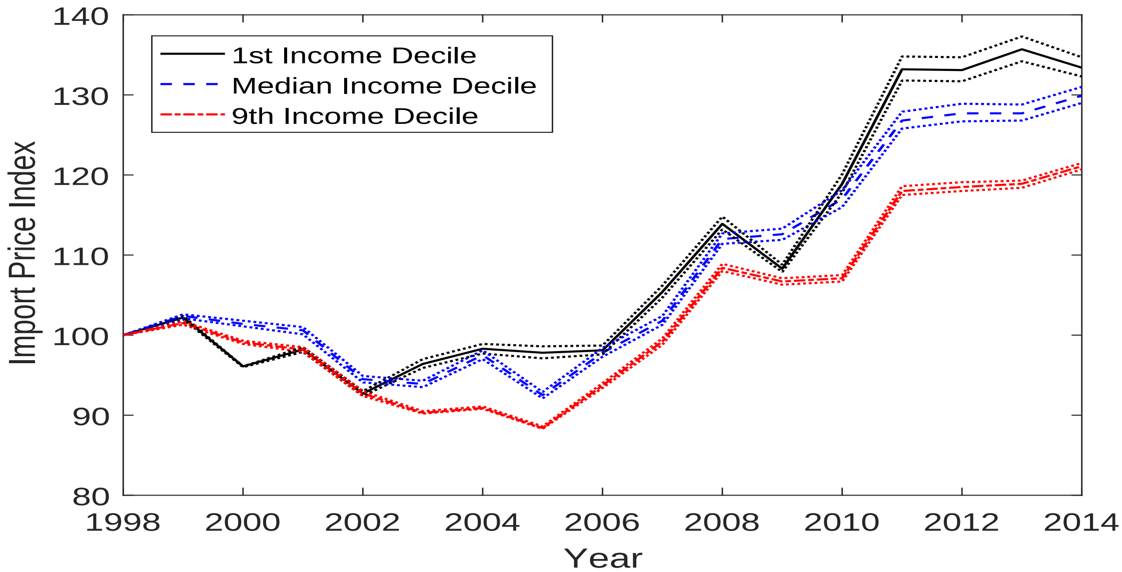


Table 6: U.S. Import Price Index, 1998-2014, by Income Decile, Selected Years

Year	1st Decile	2nd Decile	4th Decile	5th Decile	6th Decile	8th Decile	9th Decile
1998	100.0	100.0	100.0	100.0	100.0	100.0	100.0
2000	96.1	93.3	96.1	101.4	101.9	100.2	99.1
2002	92.7	91.5	91.8	94.5	94.2	93.3	92.7
2004	98.3	94.4	97.0	97.5	97.9	91.9	90.9
2006	98.1	96.5	99.1	97.8	98.4	94.6	93.7
2008	113.9	108.4	113.8	112.0	112.2	109.7	108.4
2010	118.9	113.6	113.7	117.0	115.8	108.8	107.1
2012	133.1	121.9	125.1	127.7	123.9	121.5	118.5
2014	133.4	128.5	126.5	129.9	118.3	124.6	121.1

The results are quite different from the Laspeyres benchmark. Most starkly, the lowest income decile now features the highest path for import price inflation. This difference arises because although cumulative import price inflation through 2014 is lower in our full model price index than in the Laspeyres case for all deciles, the decrease in cumulative inflation between models is smallest for lowest-income households. As shown in Table 7, average annual import price inflation for the first income decile increases by only 0.2 percentage points in the Laspeyres benchmark relative to the full model, compared to about 0.6 percentage points for the median and about 1.1 percentage points for the highest income decile. These results indicate that the upward bias in measured inflation from using a Laspeyres index is not constant across income deciles in our setting.

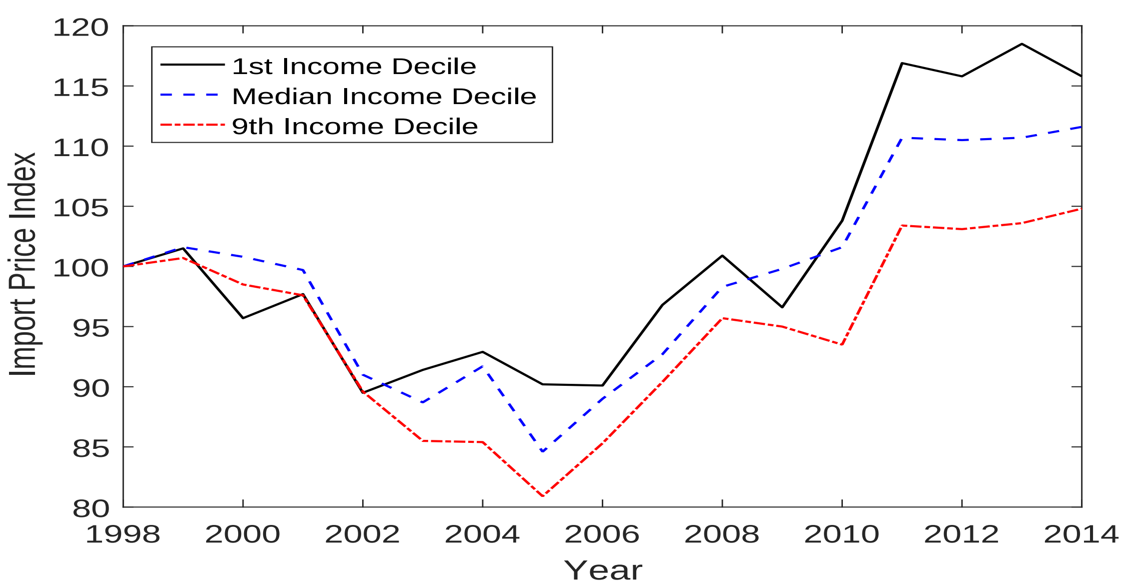
Table 7: Annual Average Import Price Inflation by Decile, 1998-2014

Decile	1	2	4	5	6	8	9
Baseline	1.82	1.58	1.48	1.65	1.06	1.38	1.20
Laspeyres	2.02	2.05	2.33	2.23	1.88	2.21	2.26

5.3 The Role of Different Products

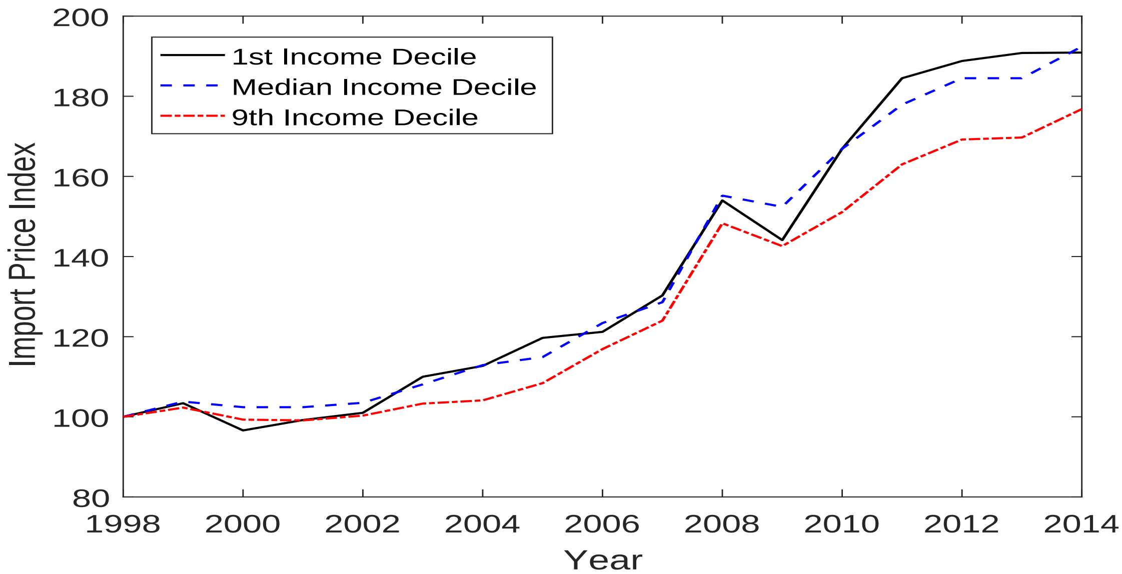
Although we have shown that the total share of income spent on imported products does not differ much across income deciles, it is still the case that the share of income spent on particular imported products differs widely across deciles. An interesting decomposition, therefore, is excluding food and energy products from the overall price index to generate a "core" import price index. As can be seen in Figure 5, this index preserves many of the same features of the baseline index, including differences across deciles.

Figure 5: U.S. Import Price Index for "Core" Products, Selected Deciles



However, the import price index for food and energy (i.e., "Non-Core") products in Figure 6 looks very different. Import price inflation was much greater for these products. Although the richest decile still has the lowest level of inflation, there are less stark differences between the median and lowest-income deciles for non-core products.

Figure 6: U.S. Import Price Index for Food and Energy Products, Various Deciles



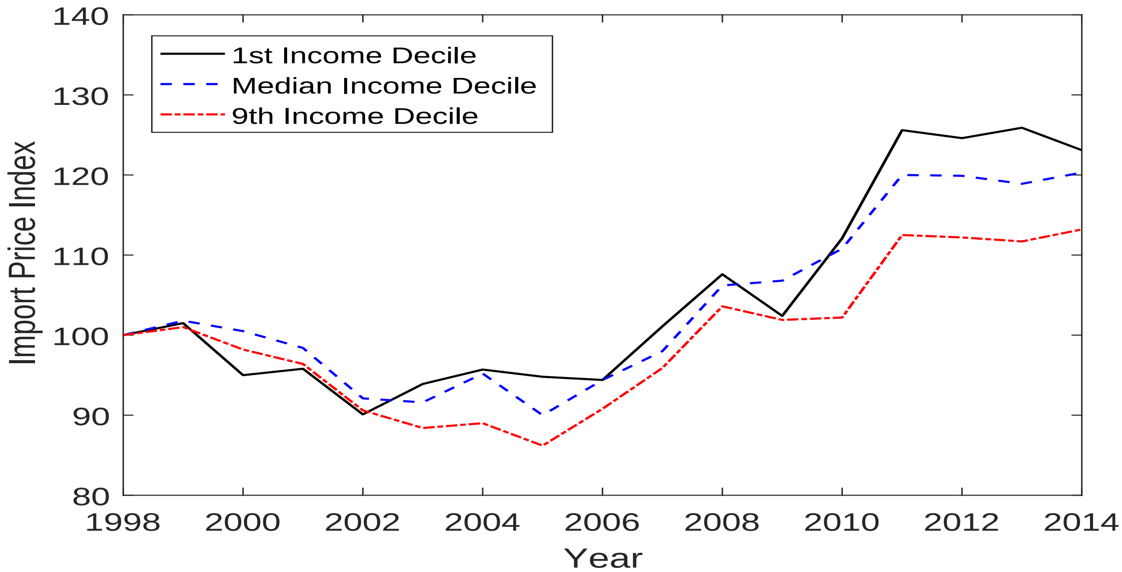
The above exercise shows that the differences in import price inflation across income groups shown in Figure 4 were not driven by food and energy products. But which sectors are mainly responsible for the differences across income groups we observe? Census disclosure rules prohibit a full accounting of the contribution to the decile-specific price indices of each individual HS4 sector. However, one exercise we can conduct is to exclude those HS4 sectors that contribute most to the difference between the lowest and highest income deciles.

To conduct the exercise, we compute household taste-adjusted sectoral price indexes, $P_{hst} \equiv [\varphi_{hst}^{\sigma-1} P_{st}^{1-\sigma}]$[26]. Then, for each sector, we take the average difference between the price indexes of the lowest income households and the highest income households over the 17 years of our sample, $\frac{1}{17} \cdot \sum_t (P_{1st} - P_{9st})$. We then drop the top 10% of sectors, ranked by this difference[27]. Figure 7 illustrates the results from constructing decile-specific import price inflation from the remaining sectors.

[26]This is the inner term of the sum in Equation 6.

[27]All of the differences in this range are positive, i.e. low income households experience greater import price inflation.

Figure 7: U.S. Import Price Index, Dropping Most Different Sectors



As expected, relative to Figure 4, the differences between the income deciles are somewhat compressed. Indeed, the difference in average annual import price inflation between the first and ninth deciles is now about 0.5 ppt. per year, compared to about 0.6 ppt. per year before. However, even after dropping the top 10 percent of sectors with the largest positive differences, the overall contour of the figure remains qualitatively similar. Therefore, we can conclude from this exercise that the differences in import price inflation across income deciles over our time period is not driven by a small number of HS4 sectors.

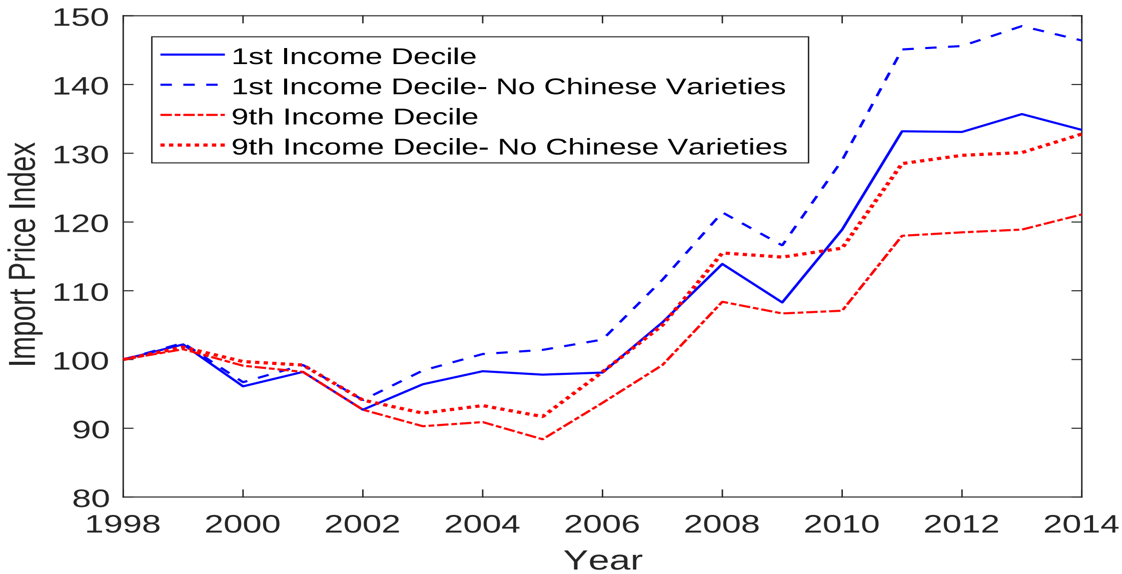
5.4 The Role of China

Another interesting question is the extent to which the well-known increase in U.S. imports from China contributed to changes in the import price index. Although our model does not permit a full general equilibrium accounting of such an exercise, we can study how the prices of all non-Chinese varieties moved over this time period, which provides a sense for how Chinese varieties contributed to overall price movements and differences in household inflation rates[28]. These results are shown in Figure 8. The figure shows that import prices would be significantly higher for both the ninth decile and the first decile of income, in the absence of imports from China. Overall, we find that annual average import price inflation of non-Chinese varieties is 2.41% for the lowest income decile and 1.79% for the ninth income

[28]Not accounting for general equilibrium effects implies that prices and sales of the rest of the world's varieties would evolve equally compared with the case with Chinese varieties included.

decile, which are both about 0.6 percentage points per year higher than the baseline results. Thus, our results suggest that greater imports of Chinese varieties over this time period directly held down import price inflation for both high-income and low-income consumers, but not differentially across income groups.

Figure 8: U.S. Import Price Index, Direct Effect of China



5.5 Adjusting the Aggregate Elasticity of Substitution

Remember that our estimate of $\sigma = 2.3$ is higher than the estimate of 1.36 from Redding and Weinstein (2017), possibly because our estimation sample for the second stage includes only those sectors that are directly consumed by households, as is clear from Equation 17. A typical parametrization of the aggregate elasticity of substitution in the literature would be $\sigma = 1$, which corresponds to Cobb-Douglas preferences. As a robustness check, we can adopt a value of σ of 1.3, which is close to the estimate from Redding and Weinstein (2017) and much closer to Cobb-Douglas preferences. We find in this case that our price index is changed in magnitude relative to the baseline, with larger differences between income groups. We interpret the results of this robustness check as suggesting that our baseline results are conservative estimates of the differences in import price inflation across income groups, given our larger-than-typical estimate of σ.

5.6 Summary of Import Price Inflation by Decile

Table 8 provides the annual average import price inflation rates experienced by each decile for the various exercises. The results show a clear pattern that higher-income households have experienced the lowest import price inflation and lower-income households the highest import price inflation over this time period.

Table 8: Annual Average Import Price Inflation by Decile, 1998-2014

Decile	1	2	4	5	6	8	9
Baseline	1.82	1.58	1.48	1.65	1.06	1.38	1.20
Core Products	0.92	0.73	0.51	0.69	0.01	0.45	0.29
Food and Energy Products	4.12	3.73	3.97	4.17	4.10	3.87	3.63
Without China	2.41	2.17	2.07	2.24	1.64	1.97	1.79
Drop Top 10 percent HS4 Sectors	1.31	1.09	0.88	1.16	1.14	0.94	0.78

6 Conclusion

How differently do various income groups experience import price inflation? This question matters for thinking about the winners and losers from international trade as well as the evolution of inequality in an open economy. This paper is the first to analyze this question for the United States. To do so, we build import price indexes with prices from about 2.6 million individual foreign supplier-HS10 observations per year in U.S. import data. The prices we use are therefore far more disaggregated than exporter country-HS10 combinations, the most typical unit of observation in other work estimating import price indexes. To construct import price indexes that vary by income decile, we estimate a structural model that incorporates cross-sector non-homotheticity, allowing for differences in sectoral expenditure shares across groups. The estimation procedure relies on data covering consumer expenditures by income decile for the United States.

Our analysis of the data reveals several interesting results. First, using unit values from the supplier trade data tends to give very similar aggregate implications as BLS survey data on actual import prices paid by importing firms, implying that disaggregated unit values can be a valid way to study trends in import prices. Second, we find that the share of imports in total expenditure does not differ dramatically across income groups, although over time, the share of imports in overall consumption increases from 1998 to 2014. Third, we find evidence of non-homotheticity across imported sectors, meaning that different income groups have different patterns of consumption across imported sectors.

We find robust evidence that lower-income households experienced the most import price inflation from 1998 to 2014, while the higher-income households experienced the least import price inflation. In our baseline results, the first income decile experienced import price inflation of about 33% from 1998 to 2014, or 1.82 percent per year. For comparison, the ninth income decile only experienced import price inflation of about 21% over that time period, or 1.20 percent per year. Our results show that the upward bias in measured inflation from using a Laspeyres index is not constant across income deciles in our setting, as the upward bias is larger for higher income households. Consequently, a first-order approximation approach understates the difference in import price inflation across income groups. We also show that imports from China held down import price inflation in the U.S. over our time period, but not differentially across income groups. We see this paper as a building block for future research that can shed more light on the distributional effects of international trade and its contribution to real income inequality in the United States.

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