Estimating Unequal Gains across U.S. Consumers with Supplier Trade Data *

Colin J. Hottman
Board of Governors of the Federal Reserve System†

Ryan Monarch
Board of Governors of the Federal Reserve System‡

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Abstract

Using supplier-level trade data, we estimate the effect on consumer welfare from changes in U.S. imports both in the aggregate and for different household income groups from 1998 to 2014. To do this, we use consumer preferences which feature non-homotheticity both within sectors and across sectors. After structurally estimating the parameters of the model, using the universe of U.S. goods imports, we construct import price indices in which a variety is defined as a foreign establishment producing an HS10 product that is exported to the United States. We find that lower income households experienced the most import price inflation, while higher income households experienced the least import price inflation during our time period. Thus, we do not find evidence that the consumption channel has mitigated the distributional effects of trade that have occurred through the nominal income channel in the United States over the past two decades.

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† *20th Street and Constitution Avenue N.W. Washington, D.C. 20551. Email: colin.j.hottman@frb.gov.*
‡ *20th Street and Constitution Avenue N.W. Washington, D.C. 20551. Email: ryan.p.monarch@frb.gov.*

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, as well as the evolution of real income inequality. Recent research has emphasized using models in which different income groups can consume goods in different proportions (non-homotheticity), with the consequence that price indices are income group-specific[1]. The literature has also highlighted four major channels that contribute to changes in the cost of living (i.e., price indices): changes in average prices (consisting of marginal cost movements and markup adjustment), product quality changes, an expansion (or contraction) in the set of available varieties, and changes in the dispersion of prices (i.e., changing opportunities for substitution)[2].

In this paper, we develop a new framework based on non-homothetic preferences that flexibly allows each of the four channels to contribute to changes in the price index, and, using detailed trade transaction data for the United States from 1998 to 2014, estimate the import price index based on that framework for different income deciles. The model permits both cross-sector and within-sector non-homotheticity, the first of which captures differences in sectoral expenditure shares across consumers and the second which captures differences in product quality. Exact linear aggregation over consumers is preserved in our framework, even with entry and exit of varieties. Our framework also nests the standard, homothetic, Constant Elasticity of Substitution (CES) monopolistic competition model as a special case.

To estimate the model parameters, we develop an extension of the Generalized Method of Moments (GMM) estimator of Feenstra (1994) which exploits the relationship between income elasticities and price elasticities for separable demand functions and apply it to data on the universe of foreign establishments exporting to the United States from 1998 to 2014. We define a variety as the combination of a foreign establishment and a Harmonized System (HS) ten-digit product code, and, consistent with the literature around this estimator, distinguish between "continuing " varieties– those found in all years 1998-2014– and non-continuing varieties. Over this time period, the number of unique imported varieties rises from 2 million in 1998 to 2.9 million in 2006, before falling again afterward to about 2.2 million by 2014.[3] We further discipline the model using income-decile specific expenditure data from the Bureau of Labor Statistics Consumer Expenditure Survey. The data show that even though the share of total expenditure spent on imports is fairly constant across income groups, there are large differences in the composition of imported

[1]See Hunter (1991), Neary (2004), Choi et al. (2009), Fajgelbaum et al. (2011), Fieler (2011), Li (2012), Handbury (2013), Markusen (2013), Caron et al. (2014), Faber (2014), Feenstra and Romalis (2014), Aguiar and Bils (2015), Simonovska (2015), Fajgelbaum and Khandelwal (2016), Jaravel (2016), Borusyak and Jaravel (2017), Cravino and Levchenko (2017), Faber and Fally (2017), and Atkin et al. (Forthcoming)

[2]For example, Feenstra (1994), Boskin et al. (1997), Bils and Klenow (2001), Hausman (2003), Lebow and Rudd (2003), Broda and Weinstein (2006), Broda and Weinstein (2010), Khandelwal (2010), Hallak and Schott (2011), Handbury and Weinstein (2014), Hsieh et al. (2016), Aghion et al. (2017), Amiti et al. (2017), Feenstra (2017), Feenstra and Weinstein (2017), and Feldstein (2017).

[3] This hump-shaped pattern for the number of imported varieties over time is new to the literature but is robust to different definitions of a variety.

consumption across income groups.

Estimating the parameters of the model yields several new results. First, we estimate sectoral elasticities of substitution squarely in line with the literature but find that the overall aggregate elasticity of substitution is close to 2.8, higher than the typically assumed value of 1. Second, we find that non-continuing, small foreign producers are often well approximated by the CES model, but continuing varieties deviate from the behavior implied by the standard CES benchmark model. In particular, the markups of these large foreign suppliers are often declining in their quantity sold, a relationship precluded by standard models [4]. Third, we find that the estimated markup of the median supplier to the United States fell from 1998 to 2014. The median markup among continuing varieties fell from 23% in 1998 to about 13% in 2006 and remained about constant thereafter.

We use our model estimates and the variety-level trade data to construct the U.S. import price index using our flexible, non-homothetic preference structure. Taking 1998 as the reference year, import prices fell nearly 12% by 2006 (the same period that the number of available varieties was increasing, and that markups fell). However, by 2014, the import price index had risen about 8% from its 1998 level. Compared with the non-variety-adjusted, non-quality-adjusted BLS import price index, our finding of a decline in import prices from 1998 through 2006 is the opposite of the published index, which shows a 25% increase.

We exploit the non-homothetic nature of our preferences to ask whether different income groups experienced different levels of import price inflation over our time period. Supplementing our model estimates with information from the BLS Consumer Expenditure Survey, we determine the consumption basket of imported goods and calculate its associated price index for different income deciles. The U-shaped pattern observed for the aggregate import price index over time is replicated for each individual income group. However, we find that lower income households experienced the most import price inflation, while higher income households experienced the least import price inflation during our time period. Given our finding that each income decile's share of expenditure on total imported goods was about the same, we do not find evidence that the consumption channel has mitigated the distributional effects of trade that have occurred through the nominal income channel as documented in Autor et al. (2016), Pierce and Schott (2016), and the related literature. Instead, changes in import prices appear to be exacerbating increases in nominal income inequality over this time period. Our results also indicate that cross-sector non-homotheticity is the key mechanism driving the differences in import inflation across import groups.

The rest of this paper is structured as follows. Section 2 reviews related literature. Section 3 outlines the model. Section 4 explains our identification strategy. Section 5 discusses our estimation results. Section 6 concludes.

[4]This relationship between markups and quantities implies that increased competition may raise the markups charged by these large foreign firms, which is the "anti-competitive" effect of trade discussed in the theoretical literature.

2 Related Literature

Most of the international economics literature has studied import price indices using homothetic preferences (e.g., Feenstra (1994), Broda and Weinstein (2006), Hsieh et al. (2016), Amiti et al. (2017), Feenstra and Weinstein (2017)). Of course, homothetic preferences preclude any focus on distributional issues across consumers[5]. We use non-homothetic preferences, which allow us to quantify the effect of changes in U.S. imports on different household income groups.

The international trade literature has highlighted two forms of non-homotheticity. First, there is sector-level non-homotheticity (e.g., Caron et al. (2014), Fajgelbaum and Khandelwal (2016)), which reflects differences in sectoral expenditure shares across income groups. Second, there is variety-level non-homotheticity (e.g., Feenstra and Romalis (2014)), which the literature has associated with differences in product quality. Our framework allows us to take into account both forms of non-homotheticity. We exactly match sector-level non-homotheticity from data on sectoral expenditure shares by income decile from the U.S. Consumer Expenditure Survey. In order to identify variety-level non-homotheticity, we estimate our model on microdata, exploiting the relationship between income elasticities and price elasticities (i.e. markups).

A growing body of theoretical work shows that how the price elasticity of demand changes with firm sales determines the nature of market distortions in monopolistic competition (Dhingra and Morrow (forthcoming)), the competitive effects of opening to international trade (Zhelobodko et al. (2012), Bertoletti and Epifani (2014), Arkolakis et al. (forthcoming)), and the pass-through of cost shocks to firms' profit margins (Mrázová and Neary (2017)). However, most existing research hard-wires how the price elasticity of demand changes with sales, and thus requires "pro-competitive" effects of trade: reduced markups of incumbents as a result of more foreign entry (and thus lower incumbent market shares). This is the case with standard preferences and market structures such as CES with oligopoly (Atkeson and Burstein (2008), Edmond et al. (2015)), Linear Demand (Melitz and Ottaviano (2008)), Logit demand (Fajgelbaum et al. (2011)), Constant Absolute Risk Aversion, or CARA, preferences (Behrens and Murata (2007), Behrens and Murata (2012)), and Almost Ideal Demand/Translog preferences (Feenstra and Weinstein (2017)). In contrast, our new framework based on the S-branch utility tree allows us to directly test, instead of impose, how markups move with quantities sold.

The markup flexibility of our model is important because the empirical literature on markup adjustment in response to trade shocks is mixed. Domestic markups have been found to decline in countries with dramatic trade liberalizations (Levinsohn (1993), Harrison (1994), Krishna and Mitra (1998)). Antidumping cases that protect domestic firms also appear to raise markups (Konings and Vandenbussche (2005)). This evidence suggests that import penetration may have pro-competitive effects. However, other recent papers have found that increased international competition may also raise domestic markups, providing estimates of anti-competitive effects (Chen et al. (2009), De Loecker et al. (2014), De Loecker et al. (2016)). None

[5] 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.

of these papers present evidence on the U.S. case. In contrast, our paper directly estimates how the price elasticity of demand varies with sales for U.S. import suppliers.

The literature has shown that markup adjustment and changes in the set of varieties available might not contribute anything to gains from trade in standard general equilibrium trade models with Pareto distributed firm productivity (Arkolakis et al. (2012), Costinot and Rodríguez-Clare (2014), Arkolakis et al. (forthcoming)). However, we do not need to impose the full general equilibrium structure of these models on the data in order to estimate the change in the U.S. import price index. Nor do we need to make assumptions about the distribution of firm productivity in order to estimate markups. In fact, our framework lies outside the class of models that these papers consider[6].

Recent papers have used scanner data to study related questions (e.g., Jaravel (2016), Borusyak and Jaravel (2017), Faber and Fally (2017)). However, standard 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). In contrast, the trade data we use captures the universe of U.S. goods imports.

The most closely related paper to ours is Fajgelbaum and Khandelwal (2016). They 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. In contrast, we use supplier-level trade data to estimate how U.S. import price indices for different income groups have changed over time in the observed data. Fajgelbaum and Khandelwal do not consider variety-level non-homotheticity (i.e., product quality differences). In our detailed micro-data, the extent of product entry and exit in each year is substantial, which breaks the exact linear aggregation over consumers in the Almost Ideal Demand model. Our non-homothetic preferences preserve Gorman polar form even with entry and exit of products. The next section outlines our theoretical framework.

3 Theoretical model

3.1 Consumers

In order to study the effect of changes in U.S. imports on the consumer welfare of different income groups, we develop a new theoretical framework that builds on the non-homothetic S-Branch utility tree representation of consumer preferences in Brown and Heien (1972). These preferences have not been widely used in the international trade literature[7]. However, the S-Branch utility tree nests as special cases preferences such as Nested CES and Generalized CES that have been used recently in the literature[8].

We consider a world of many producers, indexed by v. Each v should be thought of as a unique variety–

[6]Relative to Arkolakis et al. (forthcoming), we allow for the possible presence of some varieties for which a reservation (choke) price does not exist.

[7]However, for an early application to consumer import demand, see Berner (1977).

[8]For examples of papers that use the former, see Atkeson and Burstein (2008), Edmond et al. (2015), Hsieh et al. (2016), and Amiti et al. (2017). For the latter, see Arkolakis et al. (forthcoming), Mrázová and Neary (2017), and Dhingra and Morrow (forthcoming)

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

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

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, φ_{hst} is a demand shifter for sector s for household h at time t, σ is an elasticity parameter, and S is the set of tradable consumer goods sectors.

However, within each sector, consumers have some minimum quantity α_v of each variety v that must be consumed. In particular, the consumption index of sector s for household h at time t is

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

where q_{hvt} is the real consumption of variety v in sector s for household h at time t, φ_{vt} is a demand shifter for variety v at time t, σ^s is an elasticity parameter for sector s, α_v is the subsistence quantity required of variety v, and G_s is the set of varieties in sector s.

This complete utility function– known as the S-Branch utility tree– satisfies the regularity conditions of microeconomic theory when the direct utility function is well-behaved, and satisfies the continuity, monotonicity, and curvature conditions implied by utility maximization when

$$\sigma > 0, \qquad \varphi_{hst} > 0, \qquad \sigma^s > 0, \qquad \varphi_{vt} > 0, \qquad k_{hv} < \alpha_v < q_{hvt}, \tag{3}$$

where $k_{hv} < 0$ is defined in the appendix and is required to ensure a regular interior solution to the utility maximization problem. Allowing for $\alpha_v < 0$ extends the parameter region considered in Brown and Heien (1972)[9]. The regularity region is defined by the set of prices and sector expenditures such that $Y_{hst} > \sum_{v \in S} \alpha_v p_{vt}$. Thus, this utility function is effectively globally regular in the sense of Cooper and McLaren (1996), because the regularity region grows with real expenditure.

3.1.1 Variety-Level Demand

Maximizing household utility can be done as a two-stage budgeting process, where we first maximize the utility from sector s given a preliminary sectoral expenditure allocation. Taking sector expenditure Y_{hst} as given, the utility maximizing quantity demanded of variety v in sector s for household h at time t is

$$q_{hvt} = \alpha_v + \left(\frac{{p_{vt}}^{-\sigma^s} \varphi_{vt}^{\sigma^s-1}}{P_{st}^{1-\sigma^s}} \right) \left(Y_{hst} - \sum_{j \in G_s} \alpha_j p_{jt} \right), \tag{4}$$

[9]The admissibility of $\alpha_v < 0$ was noted by Blackorby et al. (1978), page 280.

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

$$P_{st} = \left(\sum_{j \in G_s} p_{jt}^{1-\sigma^s} {\varphi_{jt}}^{\sigma^s - 1} \right)^{\frac{1}{1-\sigma^s}}, \tag{5}$$

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. For any variety v that does not have a positive quantity sold in all time periods t, we require that $\alpha_v \leq 0$. The possibility of "negative subsistence" quantities is also a feature of Stone-Geary preferences. One interpretation of a negative α_v, as can be seen in Equation 4, is that it lowers the utility–maximizing quantity demanded of a particular variety relative to the CES case, which would correspond to $\alpha_v = 0$.

This variety-level demand system is known as the Generalized CES demand function (Pollak and Wales (1992)) or the Pollak demand function (Mrázová and Neary (2017)) and nests well-known functions as special cases. For example, the Constant Absolute Risk Aversion (CARA) demand function (Behrens and Murata (2007)) and the Linear Expenditure System (Stone-Geary) are limiting cases of the Generalized CES demand function as σ^s approaches zero and one, respectively. If all the α_v terms are zero, the Generalized CES demand function reduces to the standard CES demand function, which itself contains the Cobb-Douglas and Leontief demand systems as limiting cases as σ^s approaches one and zero, respectively. Note that in the CES case, varieties are substitutes if $\sigma^s > 1$ and complements if $\sigma^s < 1$. Finally, Mrázová and Neary (2017) note that this demand function, as perceived by a monopolistically competitive firm, reduces to Linear demand as σ^s approaches negative one. However, the Linear demand case is ruled out here by the parameter restrictions required for integrability.

The variety-level demand function 4 has important advantages for the purposes of quantifying the gains from new varieties. First, this demand system does not feature symmetric substitution patterns. Differentiating Equation 4 with respect to the price of another variety j in the same sector s and multiplying by $\frac{p_{jt}}{q_{hvt}}$ gives the following cross-price elasticity of demand[10]:

$$\frac{\partial q_{hvt}}{\partial p_{jt}} \frac{p_{jt}}{q_{hvt}} = \left(\frac{q_{hvt} - \alpha_v}{q_{hvt}}\right)\left(\frac{p_{jt}}{Y_{hst} - \sum_{j \in G_s} \alpha_j p_{jt}}\right)[(\sigma_s - 1)(q_{hjt} - \alpha_j) - \alpha_j] \tag{6}$$

It immediately follows that, in general, $\frac{\partial q_{hvt}}{\partial p_{jt}} \frac{p_{jt}}{q_{hvt}} \neq \frac{\partial q_{hkt}}{\partial p_{jt}} \frac{p_{jt}}{q_{hkt}}$, where k is a third variety in sector s[11]. Hausman (1996) argues that symmetric substitution patterns leads CES and logit demand systems to potentially overstate the gains from new varieties, because, upon entry, new varieties gain sales symmetrically from all other existing varieties. Related to this symmetry issue, Ackerberg and Rysman (2005) note that CES and logit may overstate the gains from variety because they do not feature crowding in the product space (i.e., products do not become closer substitutes as the number of products grows). It is clear from Equation 6 that the substitutability of varieties changes as the number of varieties G_s changes.

[10]Note that in this derivation we are holding sector expenditure fixed. However, as will be seen later in the paper, except in the case of a Cobb-Douglas upper tier of utility, sector expenditure will in general respond to changes in the sectoral price aggregate.

[11]However, note that Slutsky symmetry is satisfied.

Second, the consumer gain from the availability of a new variety, holding all else fixed, is the change in the indirect utility function (or price index) when the price of the new variety changes from its reservation price to the price at which it is sold in positive quantities. Unlike other standard demand functions used in the trade literature, this demand function allows for reservation prices to be finite or infinite depending on the sign of α_v. Note from Equation 4 that if $\alpha_v = 0$, then the reservation price at which variety v is demanded in zero quantity is infinite, as in the case of standard CES demand. Reservation prices are also infinite in logit-based models (Bajari and Benkard (2003)). However, if $\alpha_v < 0$, then the reservation price at which variety v is demanded in zero quantity is finite, as in the case of Translog demand. In the finite reservation price case, the reservation price is decreasing in the number of available varieties.

3.1.2 Sector-Level Demand

Having solved for the household utility-maximizing quantity demanded for each variety given a preliminary sectoral allocation, we can now solve for the utility-maximizing sectoral expenditures. First substitute Equation 4 into Equation 2, and then substitute the result into Equation 1. As in Brown and Heien (1972)[12], maximizing this resulting expression, subject to the constraint that $\sum_s Y_{hst} = Y_{ht}$, yields the utility maximizing expenditures of household h on sector s:

$$Y_{hst} = \frac{\varphi_{hst}^{\sigma-1} {P_{st}}^{1-\sigma}}{\sum_{j\in S} \varphi_{hjt}^{\sigma-1} {P_{jt}}^{1-\sigma}} \left(Y_{ht} - \sum_{s\in S} \sum_{v\in G_s} \alpha_v p_{vt} \right) + \sum_{v\in G_s} \alpha_v p_{vt}, \tag{7}$$

where Y_{ht} is the total expenditure of household h at time t and P_{st} is the sectoral price aggregate.

3.1.3 Within-Sector and Cross-Sector Non-Homotheticity

These preferences feature non-homotheticity both within and across sectors. To demonstrate within-sector non-homotheticity, multiply both sides of Equation 4 by the price of variety v, then divide both sides by the sectoral expenditure Y_{hst}. This procedure yields the following variety-level share equation:

$$s_{hvt} = \alpha_v \frac{p_{vt}}{Y_{hst}} + \left(\frac{{p_{vt}}^{1-\sigma^s} \varphi_{vt}^{\sigma^s-1}}{\sum_{j\in G_s} (\frac{p_{jt}}{\varphi_{jt}})^{1-\sigma^s}}\right)\left(\frac{Y_{hst} - \sum_{j\in G_s} \alpha_j p_{jt}}{Y_{hst}}\right), \tag{8}$$

where s_{hvt} is the expenditure share of variety v for household h at time t. It is clear from Equation 8 that Generalized CES preferences are non-homothetic: the share of expenditure spent on a particular variety v is different for households of different incomes.[13] The fact that different households can spend different shares of their income on any variety v can also be seen from the elasticity of variety demand with respect to sectoral expenditure:

[12] Note that the Brown and Heien (1972) expression for the utility-maximizing expenditure allocation had an error. Our expression for the expenditures corrects this error.

[13] In the model, there is no saving or transfers, so household income is household expenditure. We will deal with this distinction in detail in the empirical section using U.S. Census income deciles together with implied expenditure patterns for households in that decile from the Consumer Expenditure Survey.

$$\frac{\partial q_{hvt}}{\partial Y_{hst}}\frac{Y_{hst}}{q_{hvt}} = (\frac{Y_{hst}}{Y_{hst} - \sum_{j\in G_s}\alpha_j p_{jt}})(\frac{q_{hvt} - \alpha_v}{q_{hvt}}) \quad (9)$$

In fact, the Generalized CES expenditure function exhibits the Gorman Polar Form (Deaton and Muellbauer (1980)). Thus, its budget shares are not independent of the level of income, and its Engel curves are not lines through the origin. Instead, the Generalized CES demand function has linear Engel curves that are shifted to have intercepts equal to the subsistence requirements α_v. Depending on the value of α_v, the expenditure elasticity can be greater than one (luxury goods), equal to one, less than one (necessity goods), or nearly equal to zero, but not less than zero (i.e., no inferior goods). These preferences satisfy the necessary and sufficient conditions for the existence of a representative consumer.

To demonstrate the presence of cross-sector non-homotheticity, we divide Equation 7 by total household expenditure, which gives the following sector-level expenditure share equation:

$$S_{hst} = \frac{\sum_{v\in G_s}\alpha_v p_{vt}}{Y_{ht}} + \left(\frac{{P_{st}}^{1-\sigma}{\varphi_{hst}}^{\sigma-1}}{\sum_{j\in S}{P_{jt}}^{1-\sigma}\varphi_{hjt}^{\sigma-1}}\right)\left(\frac{Y_{ht} - \sum_{s\in S}\sum_{v\in G_s}\alpha_v p_{vt}}{Y_{ht}}\right) \quad (10)$$

where S_{hst} the share of total expenditure for household h spent on sector s. This equation shows that these preferences feature non-homotheticity at the sector-level as well, for two reasons. The first reason is because we allow the sector-level demand shifters (φ_{hst}) to be different across income groups, which will generate sector-level non-homotheticity even if all α terms are zero. Second, even if all income groups have the same sector-level demand shifters, the sectoral expenditure shares will differ with income long as the α terms are not all zero.

3.2 Import Price Indices

In this section, we first derive an expression for the household-level import price index. We then use the aggregation properties of the model to build up the aggregate import price index.

3.2.1 Combining Sector-Level and Variety-Level Demand

Combining Equations 4 and 7, we can write the utility-maximizing quantity demanded of variety v in sector s in terms of aggregate expenditure Y_{ht} for household h as

$$q_{hvt} = \alpha_v + (\frac{{p_{vt}}^{-\sigma^s}\varphi_{vt}^{\sigma^s-1}}{\sum_{k\in G_s}(\frac{p_{kt}}{\varphi_{kt}})^{1-\sigma^s}})(\frac{\varphi_{hst}^{\sigma-1}{P_{st}}^{1-\sigma}}{\sum_{j\in S}\varphi_{hjt}^{\sigma-1}{P_{jt}}^{1-\sigma}})(Y_{ht} - \sum_{s\in S}\sum_{k\in G_s}\alpha_k p_{kt}). \quad (11)$$

3.2.2 Household Import Price Indices

In this section, we derive expressions for the household-specific import price indices.

As shown in Blackorby et al. (1978) (pages 280 - 284), we can substitute Equation 11 into Equation 2, then substitute the subsequent expression into Equation 1, to write the indirect utility function dual to our complete direct utility function as

$$V_{ht} = \left(\sum_{s \in S} \varphi_{hst}^{\sigma-1} {P_{st}}^{1-\sigma}\right)^{\frac{1}{\sigma-1}} (Y_{ht} - \sum_{s \in S} \sum_{v \in G_s} \alpha_v p_{vt}), \tag{12}$$

where V_{ht} is indirect utility for household h at time t and P_{st} is the same sectoral price aggregate given earlier.

Re-arranging Equation 12 gives the following household expenditure function:

$$Y_{ht} = V_{ht} \left(\sum_{s \in S} \varphi_{hst}^{\sigma-1} {P_{st}}^{1-\sigma}\right)^{\frac{1}{1-\sigma}} + \sum_{s \in S} \sum_{v \in G_s} \alpha_v p_{vt}. \tag{13}$$

Picking a reference indirect utility V_{hk} to hold constant defines the following price index for household imported consumption:

$$P_{ht} \equiv V_{hk} \left(\sum_{s \in S} \varphi_{hst}^{\sigma-1} {P_{st}}^{1-\sigma}\right)^{\frac{1}{1-\sigma}} + \sum_{s \in S} \sum_{v \in G_s} \alpha_v p_{vt}, \tag{14}$$

where the change in the import price index for household h from time t to time $t+i$ can be written as

$$\frac{P_{ht+i}}{P_{ht}} = \frac{V_{hk} \left(\sum_{s \in S} \varphi_{hst+i}^{\sigma-1} {P_{st+i}}^{1-\sigma}\right)^{\frac{1}{1-\sigma}} + \sum_{s \in S} \sum_{v \in G_s} \alpha_v p_{vt+i}}{V_{hk} \left(\sum_{s \in S} \varphi_{hst}^{\sigma-1} {P_{st}}^{1-\sigma}\right)^{\frac{1}{1-\sigma}} + \sum_{s \in S} \sum_{v \in G_s} \alpha_v p_{vt}}. \tag{15}$$

Using the expenditure function to substitute in for the reference utility level V_{hk}, we can alternatively express the change in the import price index for household h from time t to time $t+i$ as

$$\frac{P_{ht+i}}{P_{ht}} = \frac{\left[\sum_{s \in S} {\varphi_{hst+i}}^{\sigma-1} {P_{st+i}}^{1-\sigma}\right]^{\frac{1}{1-\sigma}}}{\left[\sum_{s \in S} {\varphi_{hst}}^{\sigma-1} {P_{st}}^{1-\sigma}\right]^{\frac{1}{1-\sigma}}} \left(\frac{Y_{hk} - \sum_{s \in S} \sum_{v \in G_s} \alpha_v p_{vt}}{Y_{hk}}\right) + \left(\frac{\sum_{s \in S} \sum_{v \in G_s} \alpha_v p_{vt+i}}{Y_{hk}}\right) \tag{16}$$

This expression for the household-specific price index change clearly shows that households of different incomes will experience different import price inflation rates if either $\exists(\alpha_v \neq 0)$ or $\varphi_{hst} \neq \varphi_{st} \forall h$.

3.2.3 Aggregate Market Demand

In this section, we show how our household-level demand functions can be consistently aggregated up to market-level demand functions. In doing so, we primarily utilize the Gorman polar form of our variety-level household demand functions. Crucially, we show that a simple restriction on the parameters of our functional form, which will be supported by our unrestricted empirical estimates, allows us to extend the exact linear aggregation results of Gorman (1961) to the case where varieties enter and exit the data over time. To our knowledge, this is the first discussion of this issue and this theoretically consistent solution in the literature.

Specifically, we retain exact linear aggregation for our functional form with variety entry and exit under two conditions.[14] The first condition is that non-continuing varieties all have $\alpha_v = 0$. We will not initially

[14] In contrast, only exact nonlinear aggregation is retained in the implicitly additive non-homothetic CES demand system of Hanoch (1975).

impose this constraint on our estimation, but our unconstrained estimates will provide support for this condition. The second condition that we require, a standard condition with Gorman polar form, is that α_v for continuing varieties is such that each household income group buys some positive amount of each variety in each time period t that has positive sales in the aggregate at that time t.[15]. In other words, we require that $Y_{hst} > \sum_{v\in S} \alpha_v p_{vt}$ and $\alpha_v > k_{hv}$, which is the condition defined in the appendix that ensures regular interior solutions.[16]

Under these simple parameter restrictions, the exact linear aggregation over households' variety-level demand is preserved, and the market demand for variety v at time t is given by $q_{vt} = \sum_h q_{hvt}$. Market demand can be written as

$$q_{vt} = (\alpha_v n_t) + (\frac{{p_{vt}}^{-\sigma^s} \varphi_{vt}^{\sigma^s - 1}}{\sum_{j\in G_s} (\frac{p_{jt}}{\varphi_{jt}})^{1-\sigma^s}})(Y_{st} - \sum_{j\in G_s} (\alpha_j n_t) p_{jt}), \tag{17}$$

where Y_{st} is aggregate U.S. expenditure on imports in sector s and demand is aggregated over n_t households.

The representative U.S. consumer's sector-level demand will take the following form:

$$Y_{st} = \frac{\varphi_{st}^{\sigma-1} {P_{st}}^{1-\sigma}}{\sum_{j\in S} \varphi_{jt}^{\sigma-1} {P_{jt}}^{1-\sigma}} \left(Y_t - \sum_{s\in S} \sum_{v\in G_s} (\alpha_v n_t) p_{vt} \right) + \sum_{v\in G_s} (\alpha_v n_t) p_{vt}, \tag{18}$$

where Y_t is aggregate U.S. expenditure on imports.[17]

3.2.4 Aggregate Import Price Index

When we analyze household price indices, we will focus on consumer goods sectors. However, in our baseline aggregate price index results we will treat all sectors as if they were consumer facing, as in Broda and Weinstein (2006) and the subsequent literature.[18]

The expenditure function of the representative U.S. consumer is given by

$$Y_t = V_t [\sum_{s\in S} \varphi_{st}^{\sigma-1} {P_{st}}^{1-\sigma}]^{\frac{1}{1-\sigma}} + \sum_{s\in S} \sum_{v\in G_s} (\alpha_v n_t) p_{vt}. \tag{19}$$

Picking a reference indirect utility V_k, the change in the price index for aggregate imports from time t to time $t+i$ can be written as

$$\frac{P_{t+i}}{P_t} = \frac{V_k \left(\sum_{s\in S} \varphi_{st+i}^{\sigma-1} {P_{st+i}}^{1-\sigma} \right)^{\frac{1}{1-\sigma}} + \sum_{s\in S} \sum_{v\in G_s} (\alpha_v n_t) p_{vt+i}}{V_k \left(\sum_{s\in S} \varphi_{st}^{\sigma-1} {P_{st}}^{1-\sigma} \right)^{\frac{1}{1-\sigma}} + \sum_{s\in S} \sum_{v\in G_s} (\alpha_v n_t) p_{vt}} \tag{20}$$

[15] Each of our household income groups will represent multiple households that fall within the same income decile, so the property that each income group buys positive quantities of all goods with positive sales in the aggregate is not completely unrealistic. Further, these preferences can also be given a discrete choice microfoundation with a random utility model from the Generalized Extreme Value distribution (Thisse and Ushchev (2016)).

[16] We impose this condition as a constraint on our parameter estimation.

[17] We do not rely on exact linear aggregation holding at the sectoral demand level, although for the purposes of constructing an aggregate import price index we utilize the form given in the text.

[18] See Caliendo and Parro (2015) and Ossa (2015) for papers that instead use an input-output structure to treat intermediate goods differently.

3.2.5 Price Index Decomposition

A useful property that we will exploit is that the CES subcomponent of our aggregate import price index, following Hottman et al. (2016), can be linearly decomposed as below:

$$
\begin{aligned}
ln([\sum_{s\in S}\varphi_{st}^{\sigma-1}{P_{st}}^{1-\sigma}]^{\frac{1}{1-\sigma}}) = \frac{1}{N_t^S}\sum_{s\in S}(\frac{1}{N_{st}^v}\sum_{v\in G_{st}} lnp_{vt}) \\
-\frac{1}{N_t^S}\sum_{s\in S}(\frac{1}{N_{st}^v}\sum_{v\in G_{st}} ln\varphi_{vt}) - \frac{1}{N_t^S}\sum_{s\in S} ln\varphi_{st} \\
-\frac{1}{\sigma-1}lnN_t^S - \frac{1}{N_t^S}\sum_{s\in S}\frac{1}{\sigma^S-1}lnN_{st}^v \\
-\frac{1}{\sigma-1}ln(\frac{1}{N_t^S}\sum_{s\in S}\frac{(\frac{P_{st}}{\varphi_{st}})^{1-\sigma}}{\widehat{(\frac{P_{st}}{\varphi_{st}})^{1-\sigma}}}) - \frac{1}{N_t^s}\sum_{s\in S}\frac{1}{\sigma^S-1}ln(\frac{1}{N_{st}^v}\sum_{v\in G_{st}}\frac{(\frac{p_{vt}}{\varphi_{vt}})^{1-\sigma^S}}{\widehat{(\frac{p_{vt}}{\varphi_{vt}})^{1-\sigma^S}}}).
\end{aligned}
\tag{21}
$$

where N_t^S is the number of sectors at time t, N_{st}^v is the number of varieties in sector s at time t, $\widehat{(\frac{P_{st}}{\varphi_{st}})^{1-\sigma}}$ is the geometric average of the sector-level quality-adjusted prices at time t, and $\widehat{(\frac{p_{vt}}{\varphi_{vt}})^{1-\sigma^S}}$ is the geometric average of the variety-level quality-adjusted prices in sector s at time t.

In this decomposition of the CES subcomponent of the import price index, each set of terms captures different economic forces. The first term on the right-hand side is a geometric average price, which captures the prices of varieties available at time t as in a standard price index. The terms in the second row capture the geometric average sector quality and the geometric average variety quality at time t, which are often absent from standard price indices and thus give rise to a quality adjustment bias in these indices. The terms in the third row capture the number of sectors at time t and the number of varieties in the average sector at time t, which, when absent from standard price indices, give rise to a new goods bias. The terms on the final row of the decomposition above capture the dispersion in quality-adjusted prices across sectors at time t and the dispersion in quality-adjusted prices across varieties within sectors at time t, which, when absent from standard price indices, give rise to a substitution bias.

Importantly, this decomposition allows us to attribute changes in the price index to changes in quality or changes in the set of available varieties, two of the main channels the literature attributes to changes in import prices. The decomposition also separates the contribution of (geometric) average prices from the contribution of dispersion in (quality-adjusted) prices. Therefore, our model can capture all four of the major channels responsible for changing import prices, and identify which ones are most important via estimation of the model.

3.3 Firms

Firms in each sector are assumed to engage in monopolistic competition and treat the sector price index and expenditure parametrically[19]. Under this assumption, and given our demand structure, firms that sell multiple varieties in the same sector will still behave like single-variety firms. That is, equilibrium markups will vary across the varieties within a multivariety firm as if each variety was sold by a different firm in the same sector. The exposition that follows refers to firms and varieties interchangeably, as would be the case for single-variety firms.

Using Equation 17 (and as in Mrázová and Neary (2017)), the monopolistically competitive own-price elasticity of demand perceived by each firm is given by[20]

$$\varepsilon_{vt} \equiv -\frac{\partial q_{vt}}{\partial p_{vt}}\frac{p_{vt}}{q_{vt}} = (\frac{q_{vt}-\alpha_v n_t}{q_{vt}})(\sigma^s) \tag{22}$$

The curvature (convexity) of demand perceived by each monopolistically competitive firm is given by

$$\zeta_{vt} \equiv -\frac{q_{vt}\frac{\partial^2 p_{vt}(q_{vt})}{\partial^2 q_{vt}}}{\frac{\partial p_{vt}(q_{vt})}{\partial q_{vt}}} = \frac{-\frac{p_{vt}\frac{\partial^2 q_{vt}(p_{vt})}{\partial^2 p_{vt}}}{\frac{\partial q_{vt}(p_{vt})}{\partial p_{vt}}}}{\varepsilon_{vt}} = (\frac{\sigma^s+1}{\sigma^s})(\frac{q_{vt}}{q_{vt}-\alpha_v n_t}) \tag{23}$$

The first-order condition for profit maximization implies that firms set prices as a markup over marginal cost according to

$$p_{vt} = \frac{\varepsilon_{vt}}{\varepsilon_{vt}-1}c_{vt} \tag{24}$$

where c_{vt} is the marginal cost of variety v at time t. Each firm's first order condition is satisfied when $\varepsilon_{vt} > 1$, and each firm's second-order condition is satisfied when $\zeta_{vt} < 2$.

Using the equation for the own-price elasticity of demand, we can write the markup term as

$$\frac{\varepsilon_{vt}}{\varepsilon_{vt}-1} = \frac{(q_{vt}-\alpha_v n_t)(\sigma^s)}{(q_{vt}-\alpha_v n_t)(\sigma^s)-q_{vt}} \tag{25}$$

There are a few things to note about this markup term. First, markups are both variety specific and time specific. Second, even though the markup is variety specific, the only observable data needed to calculate the markup (after estimating α_v and σ^s) are the quantity sold at time t- no production function estimation is required. Finally, the markup reduces to the constant markup of $\frac{\sigma^s}{\sigma^s-1}$ if $\alpha_v = 0$.

Taking the ratio of markups for two different varieties in the same sector and subtracting one gives

$$\frac{\frac{\varepsilon_{vt}}{\varepsilon_{vt}-1}}{\frac{\varepsilon_{kt}}{\varepsilon_{kt}-1}} - 1 = \frac{(q_{kt}-\alpha_k n_t)q_{vt} - (q_{vt}-\alpha_v n_t)q_{kt}}{(q_{kt}-\alpha_k n_t)(q_{vt}-\alpha_v n_t)(\sigma^s) - (q_{kt}-\alpha_k n_t)q_{vt}}, \tag{26}$$

[19] 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.

[20] If single-product firms internalize their effect on the price index, the perceived elasticity becomes $\varepsilon_{vt} = (\frac{q_{vt}-\alpha_v n_t}{q_{vt}})[(\sigma^s) + \frac{\alpha_v n_t p_{vt} - (\sigma^s-1)p_{vt}(q_{vt}-\alpha_v n_t)}{(Y_{st}-\sum_{j\in G_s}\alpha_j n_t p_{jt})}]$.

where it can immediately be seen that a higher σ^s, all else equal, lowers the scope for differences in markups across varieties in a sector.

Differentiating the markup term in Equation 25 with respect to quantity gives

$$\frac{\partial(\frac{\varepsilon_{vt}}{\varepsilon_{vt}-1})}{\partial q_{vt}} = \frac{-(\alpha_v n_t)(\sigma^s)}{[(q_{vt} - \alpha_v n_t)(\sigma^s) - q_{vt}]^2}, \tag{27}$$

which is negative if and only if α_v is positive [21].

Trade is described as "pro-competitive" if an increase in competition via increased entry from foreign firms results in reduced market shares or quantity sold for incumbent producers and decreased markups for these incumbents. Most preference structures used in the literature either deliver a positive partial derivative of markups with respect to quantity or (as in the CES case) no change in markups at all. However, as Equation 27 shows, rather than assuming these effects, estimating α_v allows us to test whether trade is pro-competitive, anti-competitive, or neither.[22]

All of these cases are possible in general, as highlighted in recent theory (Krugman (1979), Zhelobodko et al. (2012), Mrázová and Neary (2017), Parenti et al. (2017), Dhingra and Morrow (forthcoming)). As can be seen from differentiating the markup term, firm v's markup is increasing in its quantity sold if $\alpha_v < 0$, is decreasing in its quantity sold if $\alpha_v > 0$, and is constant if $\alpha_v = 0$. Standard monopolistic competition models used in the trade literature based on demand systems such as Almost Ideal Demand or Translog (Feenstra and Weinstein (2017)), Linear demand (Melitz and Ottaviano (2008)), Logit demand (Fajgelbaum et al. (2011)), and CARA demand (Behrens and Murata (2007)) do not feature anti-competitive effects from opening to trade. Additionally, trade models based on CES demand with oligopolistic competition (Atkeson and Burstein (2008), Holmes et al. (2014), De Blas and Russ (2015), Edmond et al. (2015)) also have the feature that larger market share implies larger market power, and thus successful import penetration must have pro-competitive effects in these models.

To finish specifying the firm's cost structure, we allow marginal costs to be variable, increasing in output, and given by

$$c_{vt} = \delta_{vt}(1 + \omega_s) q_{vt}^{\omega_s} \tag{28}$$

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. Combining the first-order condition and marginal cost equations gives the following pricing equation

$$p_{vt} = \frac{\varepsilon_{vt}}{\varepsilon_{vt} - 1} \delta_{vt}(1 + \omega_s) q_{vt}^{\omega_s} \tag{29}$$

[21] In the oligopoly case of footnote 20, Equation 27 can still be either positive or negative depending on the sign and magnitude of α_v.

[22] In the empirical section, we are only using foreign producer data, so, in our context, incumbents should be interpreted as producers already exporting to the United States. This is a data constraint, not a theoretical one.

4 Empirical strategy

In this section, we describe our strategy for recovering the deep parameters of the model laid out above, using U.S. import data from 1998 to 2014. Importantly, we can estimate the parameters of the above partial equilibrium model without relying on assumptions about the distribution of firm productivity or a full general equilibrium framework.

Our estimation will proceed in two stages. In the first stage, we will estimate the parameters of the variety demand functions at the aggregate market level. To address endogeneity concerns, we extend the Feenstra (1994) approach of identification via heteroskedasticity to estimate the model directly from the aggregate data on the universe of goods suppliers exporting to the United States. As will be made clear, the only observable data needed are variety-level prices and sales.

In the second stage, we will estimate the parameters of the sectoral demand functions at the household level. We do this by supplementing the import data with additional data on the sectoral composition of the consumption baskets of different income groups from the BLS Consumer Expenditure Survey. 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 and aggregate import price indices.

4.1 Estimation Stage One

While the theory is written to accommodate arbitrarily different α's for every variety, we will specify the following empirical specification for this parameter:

$$\alpha_v = \beta_s^C \min_t (q_{vt} \mid q_{vt} > 0) \qquad \text{for } v \in G_s^C, \tag{30}$$

and

$$\alpha_v = \beta_s^E \min_t (q_{vt} \mid q_{vt} > 0) \qquad \text{for } v \in G_s^E, \tag{31}$$

where α_v is the subsistence quantity required for variety v, G_s^C is the set of varieties in sector s that constantly have positive quantities sold throughout the sample period, G_s^E is the set of varieties in sector s that enter or exit (e.g., have zero quantity sold) at some point during the sample period, and β_s^j is the parameter to be estimated that potentially differs across the two sets of varieties for sector s. We require that $\beta_s^E \leq 0$ and $\beta_s^C < 1$. These restrictions satisfy the parameter restrictions on α_v required for regularity to hold for all our observations of prices and expenditure.

For each sector, there are four deep parameters to be estimated: σ^s, β_s^C, β_s^E, and ω_s. Conditional on estimating these parameters, the remaining variety-level unobservables of α_v (subsistence quantities), φ_{vt} (demand shifters), δ_{vt} (cost shifters), $\frac{\varepsilon_{vt}}{\varepsilon_{vt}-1}$ (markups), and C_{vt} (marginal costs) can be recovered from the model's structure given the data on prices and sales.[23]

To estimate these parameters, we extend the Feenstra (1994) approach of identification via heteroskedasticity to our framework. Our extension is similar in spirit to the approach in Feenstra and Weinstein (2017). Identification via heteroskedasticity has also been proposed in other recent papers (Rigobon (2003), Lewbel (2012)).

Start from the variety-level demand equation, take the time difference and difference relative to another variety k in the same sector s. This double-differencing gives

$$\Delta^{k,t} ln(p_{vt}q_{vt} - \alpha_v n_t p_{vt}) = (1-\sigma^s)\Delta^{k,t} ln(p_{vt}) + \upsilon_{vt}, \tag{32}$$

where the unobserved error term is $\nu_{vt} = (1-\sigma^s)\left[\Delta^t \ln \varphi_{kt} - \Delta^t \ln \varphi_{vt}\right]$.

Next, start from the pricing equation. This equation can be written in double-differenced form as

$$\Delta^{k,t} \ln p_{vt} = \frac{\omega_s}{1+\omega_s}\Delta^{k,t} \ln(p_{vt}q_{vt}) + \frac{1}{1+\omega_s}\Delta^{k,t} \ln(\frac{\varepsilon_{vt}}{\varepsilon_{vt}-1}) + \kappa_{vt}, \tag{33}$$

where the unobserved error term is $\kappa_{vt} = \frac{1}{1+\omega_s}\left[\Delta^t \ln z_{vt} - \Delta^t \ln z_{kt}\right]$.

As in Feenstra (1994), the orthogonality condition for each variety is then defined as

$$G(\beta_s) = \mathbb{E}_{\mathbb{T}}\left[x_{vt}(\beta_s)\right] = 0 \tag{34}$$

where $\beta_s = \begin{pmatrix} \sigma^s \\ \beta_s^C \\ \beta_s^E \\ \omega_s \end{pmatrix}$ and $x_{vt} = \nu_{vt}\kappa_{vt}$.

This condition assumes the orthogonality of the idiosyncratic demand and supply shocks at the variety level after variety and sector-time fixed effects have been differenced out. This orthogonality is plausible because in addition to the fixed effects, we have also removed variation in prices due to markup variation and movements along upward-sloping supply curves. The remaining supply shocks take the form of idiosyncratic shifts in the intercept of the variety-level supply curve and are unlikely to be correlated with idiosyncratic shifts in the intercept of the variety-level demand curve [24] .

For each sector s, stack the orthogonality conditions to form the GMM objective function

$$\hat{\beta}_s = \arg\min_{\beta_s}\left\{G^*(\beta_s)' W G^*(\beta_s)\right\} \tag{35}$$

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. Following Broda and Weinstein (2010), we give more weight to varieties that are present in the data for longer time periods and sell larger quantities[25] . As can be seen from the estimating

[23] The number of U.S. households in a given year, n_t, is available in public data from the U.S. Census Bureau.

[24] In a robustness exercise reported below, we show that our estimates do not change very much when we only estimate using a sample of multi-variety firms, and take differences relative to another variety within the same firm, in order to remove firm-time fixed effects from the supply and demand error terms.

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

equation above, the necessary observables to estimate the model are supplier-product quantities q_{vt} and sales $p_{vt}q_{vt}$. Supplier-product prices p_{vt} can be obtained by dividing revenues by quantities to form unit values.

To see how the parameters are identified, rewrite the orthogonality condition that holds for each variety and rearrange to get

$$\begin{aligned}\mathbb{E}_{\mathbb{T}}[(\Delta^{k,t}\ln p_{vt})^2] = \frac{\omega_s}{(1+\omega_s)}\mathbb{E}_{\mathbb{T}}[\Delta^{k,t}\ln(p_{vt}q_{vt})\Delta^{k,t}\ln p_{vt}] \\ -\frac{1}{\sigma^s-1}\mathbb{E}_{\mathbb{T}}[\Delta^{k,t}\ln p_{vt}\Delta^{k,t}ln(p_{vt}q_{vt}-\alpha_v n_t p_{vt})] \\ +\frac{\omega_s}{(1+\omega_s)(\sigma^s-1)}\mathbb{E}_{\mathbb{T}}[\Delta^{k,t}\ln(p_{vt}q_{vt})\Delta^{k,t}ln(p_{vt}q_{vt}-\alpha_v n_t p_{vt})] \\ +\frac{1}{(1+\omega_s)}\mathbb{E}_{\mathbb{T}}[\Delta^{k,t}\ln p_{vt}\Delta^{k,t}\ln(\frac{\varepsilon_{vt}}{\varepsilon_{vt}-1})] \\ +\frac{1}{(1+\omega_s)(\sigma^s-1)}\mathbb{E}_{\mathbb{T}}[\Delta^{k,t}ln(p_{vt}q_{vt}-\alpha_v n_t p_{vt})\Delta^{k,t}\ln(\frac{\varepsilon_{vt}}{\varepsilon_{vt}-1})]\end{aligned} \tag{36}$$

This estimating equation shows the importance of heteroskedasticity. If the variances and covariances in this equation are the same across the different varieties in a given sector, then there is not identification. However, if the variances and covariances differ across varieties, then pooling the observations of these moments across varieties in a sector allows for identification of the four common sector-level parameters, so long as there more varieties in the sector than parameters.

Finally, at this point we recover the variety-level demand shifters. In the spirit of Redding and Weinstein (2016), we normalize the demand shifter for the geometric average firm-product to be one for all time periods. Thus, we normalize $\widetilde{\varphi_{kt}} = \widetilde{\varphi_k} = 1$ across firm-products, where the tilde denotes the geometric average. The demand shifters for all firm-products can be computed using

$$\varphi_{vt} = exp\{\frac{ln(p_{vt}q_{vt}-\alpha_v n_t p_{vt}) - ln(\widetilde{p_{kt}q_{kt}-\alpha_k n_t p_{kt}}) + (\sigma^s-1)(lnp_{vt} - ln\widetilde{p_{kt}})}{\sigma^s-1}\}, \tag{37}$$

where $\widetilde{(p_{kt}q_{kt}-\alpha_k n_t p_{kt})}$ is the geometric average of $(p_{kt}q_{kt}-\alpha_k n_t p_{kt})$ across varieties in the sector at time t.

4.2 Estimation Stage Two

Given the previously estimated parameters, we can now estimate σ in the following way. First, we must construct Y_{hst}, the expenditure on imports by HS4 sector s for household h. We leave the specific details to the data section, but broadly, we construct the variable using the BLS Consumer Expenditure Survey and the trade data. Then, starting from the household sector-level demand equation, take the time difference and difference relative to another sector k bought by the same household h. This double-differencing gives

$$\Delta^{k,t}ln(Y_{hst} - \sum_{v\in G_s}\alpha_v n_t p_{vt}) = (1-\sigma)\Delta^{k,t}ln(P_{st}) + \upsilon_{hst}, \tag{38}$$

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.

We expect that running Ordinary Least Squares on the above equation would probably 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). Note that, as in section 3.2.5, the change in the log of the sectoral price index can be linearly decomposed into four terms as follows:

$$\Delta^{k,t} lnP_{st} = \Delta^{k,t}(\frac{1}{N_{st}^{v}} \sum_{v \in G_{st}} lnp_{vt}) - \Delta^{k,t}(\frac{1}{N_{st}^{v}} \sum_{v \in G_{st}} ln\varphi_{vt}) - \Delta^{k,t}\frac{1}{\sigma^{S}-1} lnN_{st}^{v} - \Delta^{k,t}\frac{1}{\sigma^{S}-1} ln(\frac{1}{N_{st}^{v}} \sum_{v \in G_{st}} \frac{(\frac{p_{vt}}{\varphi_{vt}})^{1-\sigma^{S}}}{\widetilde{(\frac{p_{vt}}{\varphi_{vt}})^{1-\sigma^{S}}}}),$$

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 38.

Given an estimate of σ, we can then solve for the household-specific sectoral demand shifters (φ_{hst}), which can be done by normalizing $\widetilde{\varphi_{hkt}} = \widetilde{\varphi_{hk}} = 1$ across sectors and using

$$\varphi_{hst} = \exp\{\frac{ln(Y_{hst} - \sum_{v \in G_s} \alpha_v n_t p_{vt}) - ln(\widetilde{Y_{hkt} - \sum_{v \in G_k} \alpha_v n_t p_{vt}}) + (\sigma - 1)(lnP_{st} - ln\widetilde{P_{kt}})}{(\sigma - 1)}\} \tag{39}$$

4.3 Data

4.3.1 Trade Data

The main 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 or exports 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.[26] There are typically close to 40 million transactions per year.

We utilize 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, port information, country of origin, and a code identifying the foreign supplier. Known as the *manufacturing ID*, or *MID*, the foreign partner identifier contains limited information on the name, address, and city of the foreign supplier.[27] Monarch (2014) and Kamal and Monarch (2017) 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

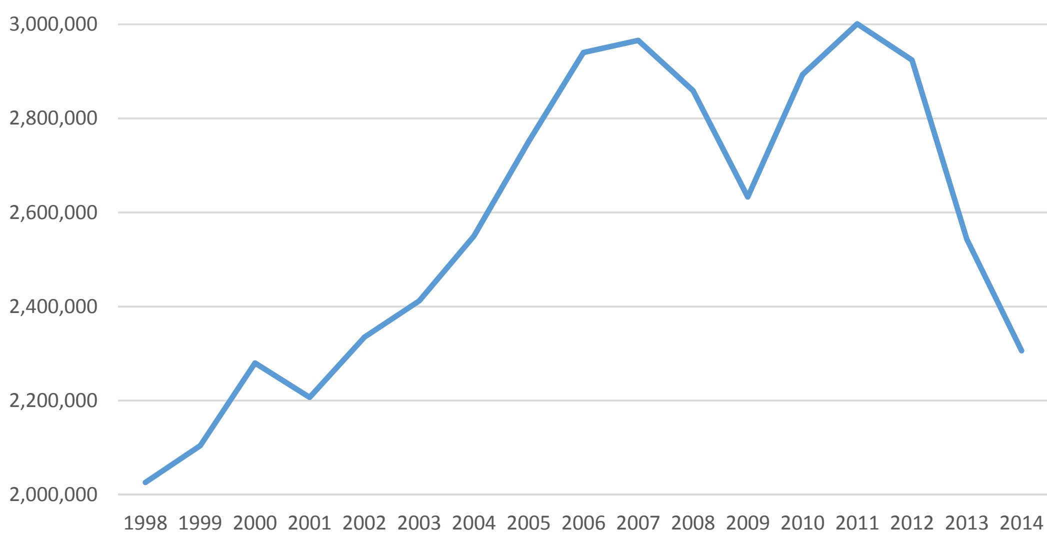
[26] Approximately 80 to 85 percent of these customs forms are filled out electronically (Kamal and Krizan (2012)).

[27] 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.

exporter 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 exporters.

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. This reduction leaves close to 40 million unique varieties (supplier-HS10 product combinations) exporting to the United States in the years 1998 to 2014. Figure 1 presents a snapshot of the number of varieties over different years in our sample- interestingly, the number of varieties increases dramatically between 1998 and 2007 before declining, rising, and declining again in the latter half of our time period.

Figure 1: Number of Imported Varieties in the U.S., 1998-2014

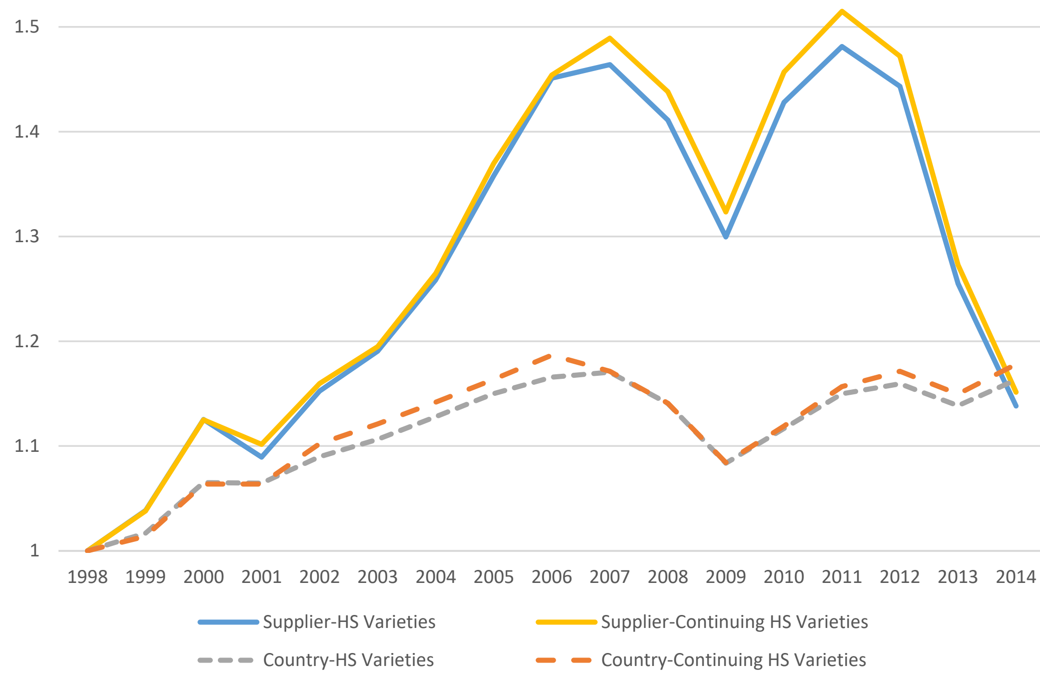


This pattern is new to the literature, so we check it against a number of other similar measures of variety. First, we compare this number to a more traditional definition of a variety in Figure 2 using publicly available Census data on the number of country-HS combinations imported by the U.S.[28] Although growth is more muted than in the more disaggregated case (as there are typically multiple suppliers per country), the overall contour is also very similar, with the exception of the change from 2013 to 2014. Second, motivated by the potential for changes in HS codes over time (as documented by Pierce and Schott (2009)) to affect our results, we confirm that this pattern holds even when only using those HS codes that are present in all years of the data, defining a variety as a supplier in a continuing HS code (the yellow line) and a country in a continuing HS code (the orange line). Correcting for entering and exiting HS codes does cause the level of varieties to shrink by close to one-third, but does little to change the time series pattern of the respective

[28]These data are described in Schott (2008) and are available from `http://faculty.som.yale.edu/peterschott/sub_international.htm`.

variety measures.

Figure 2: Number of Imported Varieties in the U.S., relative to 1998



We estimate 36 using the trade data. The estimation is performed on a reduced sample of varieties, as a large number of supplier-HS10 combinations only appear once. Thus, for our cleaned sample, we use only those varieties that are present for six or more years of data. Furthermore, as Equation 36 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. We also drop any HS4 sector that features fewer than 30 varieties over our 17 years of data. Note that with the exception of our parameter estimation sample, all our results will use the universe of goods varieties in the U.S. import data.

We run our estimation routine on each HS4 sector where there are enough observations to do so, which amounts to about 980 HS4 sectors and over 95% of total U.S. goods imports. The parameters are estimated using a nonlinear solver to solve the GMM problem described above for each of 980 HS4 sectors. We directly impose constraints on this nonlinear estimation[29]. 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.

[29]We impose the following constraints: $\varepsilon_{vt} \geq 1.01$, $\omega_s \geq 0$, $\zeta_{vt} \leq 1.99$, $\beta_s^E \leq 0$, $\beta_s^C < 1$, and $k_{hv} < \alpha_v$, the last of which is the condition defined in the appendix.

4.3.2 Consumer Expenditure Survey Data

The next step is to move to estimating the sectoral demand equations at the household level. Here we present the detailed procedure for constructing the household-specific expenditure on imports in an HS4 sector, Y_{hst}.

The BLS Consumer Expenditure Survey (CE) public data provides information on how 10 income deciles allocate their expenditure across different CE categories, beginning in 2014 (prior years have quintile figures). The CE is the data that underlie the category expenditure weights in the U.S. Consumer Price Index. In order to utilize the decile expenditure information along with our parameters estimated at the HS4 level, we undertake the following steps:

1. Begin with public U.S. Census Bureau estimates for income levels for each decile and year, 1998 to 2014.

2. Construct expenditure-to-income (EI) ratios for different income levels using public data from the CE in each year.

3. Apply the EI ratios to the Census income numbers by decile to obtain expenditure in every year for every decile.

4. Apply the 2014 decile-specific expenditure shares across CE categories to each year's decile total expenditure.

5. Concord the CE categories to HS4 codes to get household-specific expenditure on each HS4 category.

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

Steps 1-4 are a workaround to the fact that the BLS only provides decile-specific total expenditure and category expenditure shares for 2014. It is encouraging that the category expenditure shares by quintile do not change significantly from 1998 to 2013.

For Step 2, we take income levels from Census data and construct expenditure-to-income ratios using the appropriate annual income-group from the BLS Consumer Expenditure Survey. For example, the first 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 in 1998 to be \$22,691.64. We generate total expenditures by applying these EI ratios to the income data by decile (Step 3)- the implied expenditure numbers appear reasonably free from large year-to-year swings.[30] After this, we apply the decile-specific category expenditure shares from 2014 to each of these implied total decile expenditure numbers (Step 4).

[30] The expenditure numbers are included in Table 16 in the Appendix.

For Step 5, we use a concordance between the categories in the CE and Harmonized System categories developed by Furman et al. (2017).[31] An important fact to note here is that only about 20% of HS4 sectors can be found in consumer expenditures- the rest are intermediate inputs. In the end, we will use 228 HS4 sectors in the household price indices. However, we find that 54.6% 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 category.

Step 6 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). Thus, household-specific expenditure on imports from sector s are given by

$$Y_{hst} = E_{hst}(\frac{M_{s,t}}{G_{s,t} - X_{s,t} + M_{s,t}}), \tag{40}$$

where E_{hst} is the sector-level expenditure by household h from the CE, $M_{s,t}$ 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 $X_{s,t}$.[32] Also, to clarify notation, summing Y_{hst} across sectors will result in total expenditure on imports, not total expenditure in the CEX, which we will refer to as $TotExp_{ht}$.

We find several interesting facts from our Y_{hst} calculation.[33] First, the share of imports in total expenditure (i.e., $\frac{\sum_s Y_{hst}}{TotExp_{ht}}$) 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 point. Thus, any differences in price indices across income groups can be meaningfully compared because there are small differences in import shares. Table 1 shows the share of total expenditure on imports across 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

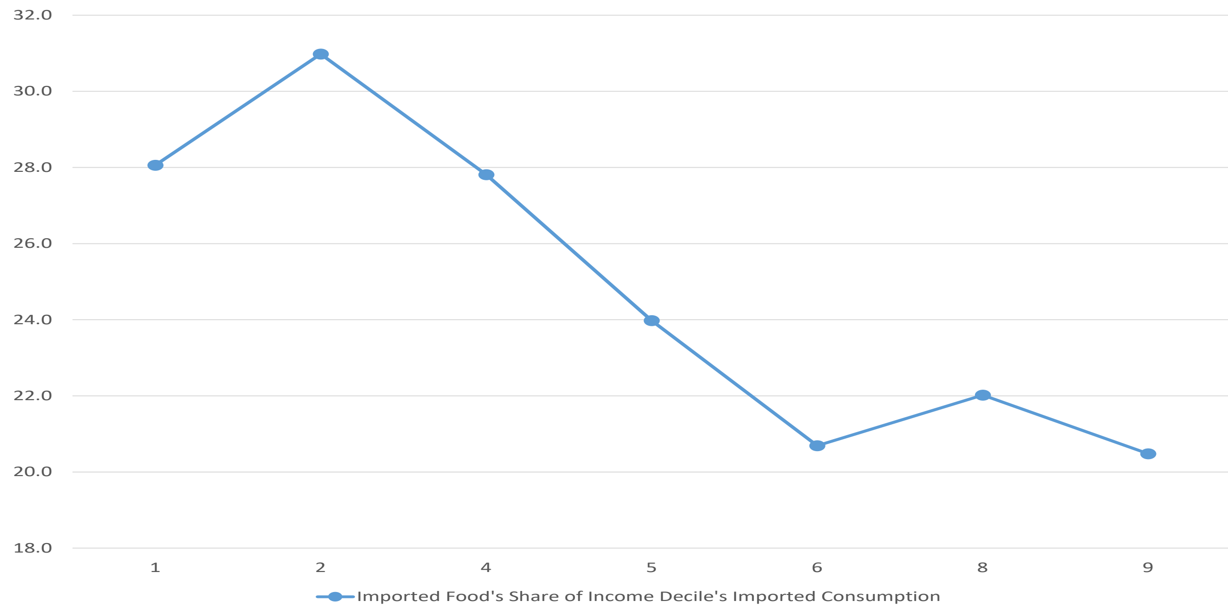
Second, non-homotheticity across broad imported sectors is evident from the data. As one example, for each household, we create the ratio of expenditure on CEX-HS4 concorded imported food as a share of total CEX-HS4 concorded imports: $\sum_{s \in Food} Y_{hst} / \sum_s Y_{hst}$. Figure 3 shows the differences across income deciles for spending on imported food: there are indeed large differences across income groups.

[31] 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.

[32] $G_{s,t}$ 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.

[33] The calculations in this paragraph rely on the version of Y_{hst} constructed using public trade data for $M_{s,t}$ and $X_{s,t}$.

Figure 3: Imported Food as a Share of Imported Consumption by Income Decile in 2014



Another way to show this fact is to compare expenditure in HS4 categories as a share of total HS4 expenditures (i.e., $\frac{Y_{hst}}{\sum_s Y_{hst}} \equiv \frac{Y_{hst}}{Y_{ht}}$) across income deciles. Table 2 presents summary statistics across HS4 categories, weighted by expenditure in an HS4. Again, 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 ($\frac{Y_{10st}/Y_{9t}}{Y_{1st}/Y_{1t}}$). 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 ($\frac{Y_{9st}/Y_{9t}}{Y_{1st}/Y_{1t}}$)

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 ($\frac{Y_{9st}/Y_{9t}}{Y_{5st}/Y_{5t}}$)

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 ($\frac{Y_{2st}/Y_{2t}}{Y_{5st}/Y_{5t}}$)

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 ($\frac{Y_{2st}/Y_{2t}}{Y_{1st}/Y_{1t}}$)

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

With Y_{hst} constructed, we work with Equation 38 to obtain σ and φ_{hst}, giving us everything we need to make the household-specific import price indices.

5 Estimation Results

We use the supplier-level data to estimate the sector-level parameters of the model and use them to construct import price indices in the aggregate and for different income groups.

5.1 Parameter Estimates

We start with estimates of σ^s, which is the sectoral-level elasticity of substitution that is comparable to estimates from Broda and Weinstein (2006). In all sectors our estimate of σ^s is statistically different from zero at the 5 percent level or better. We also find that $\sigma^s > 1$ in all sectors. Across sectors, our estimates of the elasticity of substitution have a median of 4.9, squarely in line with earlier findings for U.S. imports [34].

Table 3: Summary of σ^s

10%	Median	90%
3.06	4.93	8.59

Table 4 reports our estimate of σ, which is the aggregate-level elasticity of substitution. 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 from the presence of an endogeneity bias in this setting, the OLS estimate is biased toward zero. The IV estimate of σ is about 2.8, with a 95 percent confidence interval between 2.6 and about 3. Note that most papers in the 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 4: Estimates of σ

OLS estimate	IV estimate	IV 95% C.I.
0.82	2.78	(2.60 - 2.97)

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 statistically different from zero at the 5 percent level or better. Again, our estimated parameters are in line with previous work [35].

The next objects of interest are our α_v parameters. Remember that β_s^C and β_s^E are the sector-specific common slopes of α_v, and that, according to Equation 27, $\alpha_v < 0$ implies that markups are increasing in

[34] 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.

[35] 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 HS8 estimates in Soderbery (2015), then the 10th percentile value of ω_s is 0.03, the median is 0.30, and the 90th percentile is 14.09.

Table 5: Summary of ω_s

10%	Median	90%
0.16	0.44	1.59

quantity sold (i.e., pro-competitive effects of trade).

We start by discussing the α terms that represent continuing firms. These are the biggest, most important suppliers, as β_s^C is only able to be estimated in sectors where there are some suppliers present for every year of the sample. These results are reported in Table 6. The median β_s^C across sectors is positive, and 91% of HS4 sectors have positive values, meaning that in many cases, markups are decreasing in quantity sold (i.e. trade can be anti-competitive).[36]

Table 6: Summary of β_s^C (Continuers)

10%	Median	90%
9.96 × E-5	0.33	0.39

Remember also that $\alpha_v = 0$ would be consistent with CES preferences. In fact, 85% of sectors have values of β_s^C that are statistically significant at the 5 percent level or better, demonstrating that for this sample of continuers, CES is not a good way of summarizing their behavior.

On the other hand, β_s^E is tied to the behavior of firms who do not trade in every period- typically marginal suppliers who trade much less and are much smaller in size. As can be seen from Table 7, for these firms, CES does indeed appear to be a reasonable assumption- β_s^E must be (weakly) negative by definition, but the vast majority of sectors have estimates extremely close to zero. [37]

Table 7: Summary of β_s^E (Non-Continuers)

10%	Median	90%
-5.97 × E-5	-2.55 × E-9	-1.08 × E-10

Before moving on to discuss how we use these parameter values, we circle back to discuss the implications of relaxing the exclusion restriction at the heart of our Feenstra (1994) style estimation approach. Recall the identifying assumption that the idiosyncratic demand shocks (which are functions of φ_{vt}) and supply shocks (which are functions of δ_{vt}) at the variety level are assumed to be orthogonal after variety and sector-time fixed effects have been differenced out. There is some potential for these shocks to be correlated, however, whereby an increase in a variety's quality relative to another ($\Delta^{k,t}\varphi_{vt} \uparrow$) leads to an increase in the intercept of the cost function for that variety relative to the same comparison ($\Delta^{k,t}\delta_{vt} \uparrow$). Hottman et al. (2016) avoid this issue with Nielsen data using reference varieties *within multi-product firms* in the double-difference procedure rather than simply a reference variety within the same sector. In the spirit of their approach, we

[36] Although there is little prior work with which to compare these estimates, Arkolakis et al. (forthcoming) reports estimates of α_v parameters for U.S. imports at the HS2 digit sector level of which the median estimate is negative, the 25th percentile estimate is negative, and the 75th percentile estimate is positive.

[37] Hottman et al. (2016), using an oligopoly model and U.S. scanner data, find similar results, in the sense that large firms are found to quantitatively deviate from the CES benchmark while small firms do not.

estimate our parameters using multi-product suppliers. The estimation sample drops significantly, primarily because the only identifying variation within a sector now comes only from those suppliers with multiple varieties within the same HS4 sector. That said, the parameter values are quite similar to the baseline. Thus, our results are robust to this more exacting specification.

Table 8: Parameter Estimates using Multi-Variety Exporters

	10%	Median	90%
σ^s	1.73	4.17	9.60
β_s^C	-0.74	0.33	0.43
β_s^E	-0.89	-1.91 × E-9	-1.73 × E-10

As another robustness check, we can re-estimate our parameters by alternatively specifying the supply equation in our Feenstra (1994) estimation to include oligopolistic market power in the markup term (so markups depend on the elasticity in footnote 20 instead of the baseline equation 22). The results of this alternative estimation are reported in Table 9. Our results are qualitatively unchanged from the baseline.

Table 9: Parameter Estimates using Oligopolistic Exporters

	10%	Median	90%
σ^s	3.02	4.62	9.18
β_s^C	-0.53	0.08	0.23
β_s^E	-0.03 × E-2	-1.36 × E-9	-1.52 × E-10
ω_s	0.14	0.40	1.48

So far, we have seen that markups are often decreasing in quantity sold ($\alpha_v > 0$), trade can be anti-competitive, and the implications of CES preferences hold up much better for the behavior of marginal firms as opposed to infra-marginal firms.

5.2 Markups

Using the estimated parameter vector, we can also generate the expression $\frac{\varepsilon_{vt}}{\varepsilon_{vt}-1}$ according to Equation 25 for every supplier at every time.

We first illustrate how markups vary across sectors. To summarize this statistic, within each sector, we weight the variety-specific markup by its total trade weight within that sector over all years of data and create a sector-level summary statistic. Table 10 shows the summary of this variable across HS4 sectors. As can be seen in the table below, the median markup is about 25% over marginal cost, with the low end close to 13% and the high end at 48%.[38]

Table 10: Markup Variation across HS4 Sectors ($\frac{\varepsilon_{vt}}{\varepsilon_{vt}-1}$)

	10%	Median	90%
Sales-Weighted Average	1.132	1.250	1.482

[38]For comparison, Feenstra and Weinstein (2017) estimate a median markup across HS4 digit U.S. import sectors in 2005 of 30% over marginal cost.

We can also how see the average markup changes over time. Here we simply take the sales-weighted median markup over all varieties sold in each year and track how this median moves over time. As can be seen in Table 11, the median markup declined over the first half of the sample before flattening out from 2010 onward. Given our earlier results showing that markups are often decreasing in quantity sold, these markup declines in the early part of our sample likely reflect a large increase in imports in early years, followed by a leveling off.[39]

Table 11: Median Markup Over Time (Sales-Weighted)

Year	1998	2002	2006	2010	2014
Markup	1.235	1.226	1.215	1.215	1.215
Markup- Continuers	1.234	1.174	1.134	1.130	1.132

For robustness, we can also report the markup results implied by the oligopoly specification from Table 9. While average markups are slightly higher in the oligopoly case, the results in terms of how the average markup changes over time are unchanged from the baseline. This can be seen in Table 12 below.

Table 12: Median Markup Over Time (Sales-Weighted): Oligopoly case

Year	1998	2002	2006	2010	2014
Markup	1.256	1.251	1.237	1.235	1.235
Markup- Continuers	1.288	1.260	1.224	1.180	1.192

5.3 Aggregate Import Price Index

With our parameter estimates in hand, we can calculate the aggregate import price index for the United States from 1998 to 2014. The exercise is similar to that of Broda and Weinstein (2006) but with the two key differences that prices (and thus varieties) are supplier specific and that the preferences used here are a more flexible, non-homothetic generalization of the CES preferences used in their study. We calculate the aggregate import price index for each year from 1999 to 2014, with 1998 as the reference year.

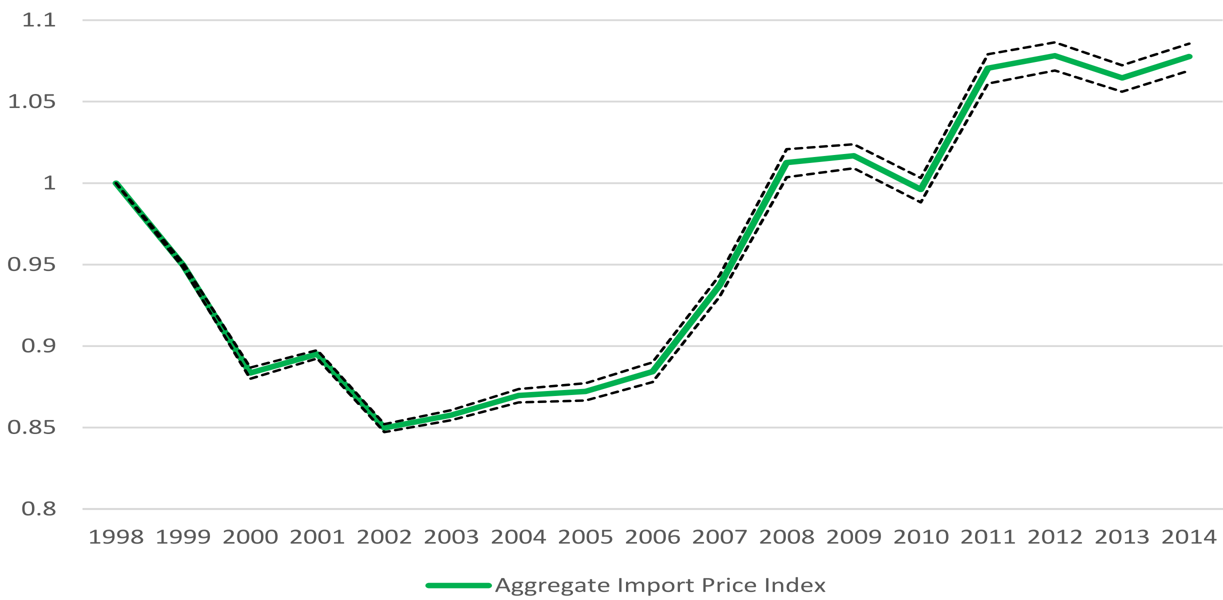
5.3.1 Baseline Results

The results are shown in Figure 4. The value of the price index in each year is also reported in table form in the Appendix. The dashed lines in the figure represent error bands, computed by recalculating the aggregate import price index using values of σ that represent the 95% thresholds for this parameter shown in Table 4. We find a U-shaped pattern: by 2006, import prices were nearly 12% lower than in 1998. However, by 2014, prices are about 8% higher than in 1998. The fall in the import price index in the early part of the period is consistent with the large increase in the number of foreign varieties observed over this time period as well as the decrease in median markups.

Figure 5 again plots our estimated aggregate import price index from 1998 through 2014, with 1998 normalized to one. For comparison, the figure also plots the BLS all-commodity import price index, which

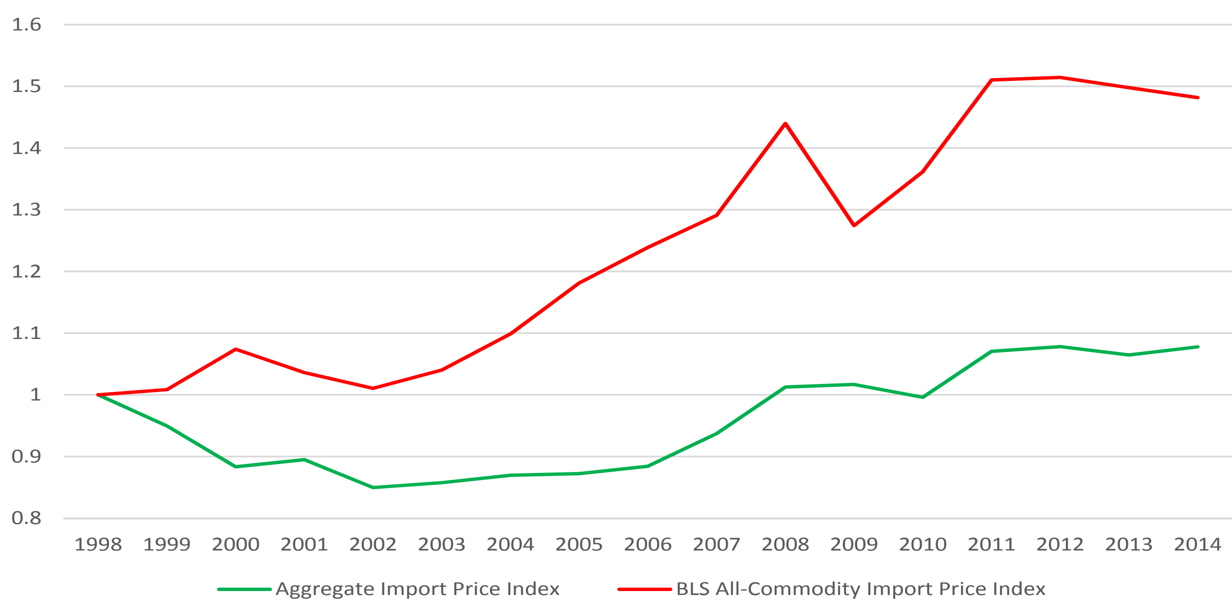
[39] Feenstra and Weinstein (2017) also estimate that markups have declined in U.S. import sectors between 1992 and 2005.

Figure 4: U.S. Import Price Index, 1998-2014



is a Laspeyres price index constructed from survey data gathered through the International Price Program. Interestingly, the decline in our aggregate import price index from 1998-2006 is in contrast with the published import price index from the BLS, which rises over this time period. Of course, the BLS price index is not variety adjusted or widely quality adjusted and likely suffers from a substitution bias from the base period weights used in the Laspeyres formula [40].

Figure 5: U.S. Import Price Indexes, 1998-2014



[40] Our import price index nests a Laspeyres index as a limiting special case when $\boldsymbol{\alpha}_v = \mathbf{0}$, $\varphi_{vt} = \varphi_v$, $\varphi_{st} = \varphi_s$, $\sigma^s \rightarrow \mathbf{0}$, and $\sigma \rightarrow \mathbf{0}$, as shown in Redding and Weinstein (2016).

To summarize, we find that the aggregate import price index, with 1998 normalized to 1, was about 1.08 in 2014. For comparison, the all-commodity import price index from the BLS, which with 1998 normalized to 1, takes a value of about 1.48 in 2014. The ratio of the two, 1.48/1.08, implies an upward bias in the Laspeyres import price index over our time period of about 37%, or about 2 percentage points per year.[41]

5.3.2 Components of the Aggregate Import Price Index

Recall from Equation 21 that we can break down our import price index into a few major components. In particular, the CES portion of the price index can be written as

$$\begin{aligned} ln([\sum_{s\in S}\varphi_{st}^{\sigma-1}{P_{st}}^{1-\sigma}]^{\frac{1}{1-\sigma}}) = \frac{1}{N_t^S}\sum_{s\in S}(\frac{1}{N_{st}^v}\sum_{v\in G_{st}} ln p_{vt}) \\ -\frac{1}{N_t^S}\sum_{s\in S}(\frac{1}{N_{st}^v}\sum_{v\in G_{st}} ln\varphi_{vt}) - \frac{1}{N_t^S}\sum_{s\in S} ln\varphi_{st} \\ -\frac{1}{\sigma-1} ln N_t^S - \frac{1}{N_t^S}\sum_{s\in S}\frac{1}{\sigma^S-1} ln N_{st}^v \\ -\frac{1}{\sigma-1} ln(\frac{1}{N_t^S}\sum_{s\in S}\frac{(\frac{P_{st}}{\varphi_{st}})^{1-\sigma}}{\widehat{(\frac{P_{st}}{\varphi_{st}})^{1-\sigma}}}) - \frac{1}{N_t^s}\sum_{s\in S}\frac{1}{\sigma^S-1} ln(\frac{1}{N_{st}^v}\sum_{v\in G_{st}}\frac{(\frac{p_{vt}}{\varphi_{vt}})^{1-\sigma^S}}{\widehat{(\frac{p_{vt}}{\varphi_{vt}})^{1-\sigma^S}}}). \end{aligned} \tag{41}$$

This equation illustrates how we can consider what factors contributed to the U-shaped trend we observe in our price index.[42] For example, we can look at the geometric average of observed variety-level prices, the first term of the price index breakdown in Equation 41. This excludes factors such as the changes in the (average) number of varieties N_{st}^v in the third line and changes in the dispersion of variety-level prices $\frac{(\frac{p_{vt}}{\varphi_{vt}})^{1-\sigma^S}}{\widehat{(\frac{p_{vt}}{\varphi_{vt}})^{1-\sigma^S}}}$ in the fourth line. If the geometric average of prices is very different from the actual import price index, this is a clue that these two factors matter for the difference. As another example, the third line of Equation 41 is key for understanding the role of new varieties: one can hold the (average) number of varieties per sector fixed at 1998 levels and trace out an alternative import price index consistent with such an experiment, illustrating how much the changing set of available varieties in the average sector contributed to these changes.

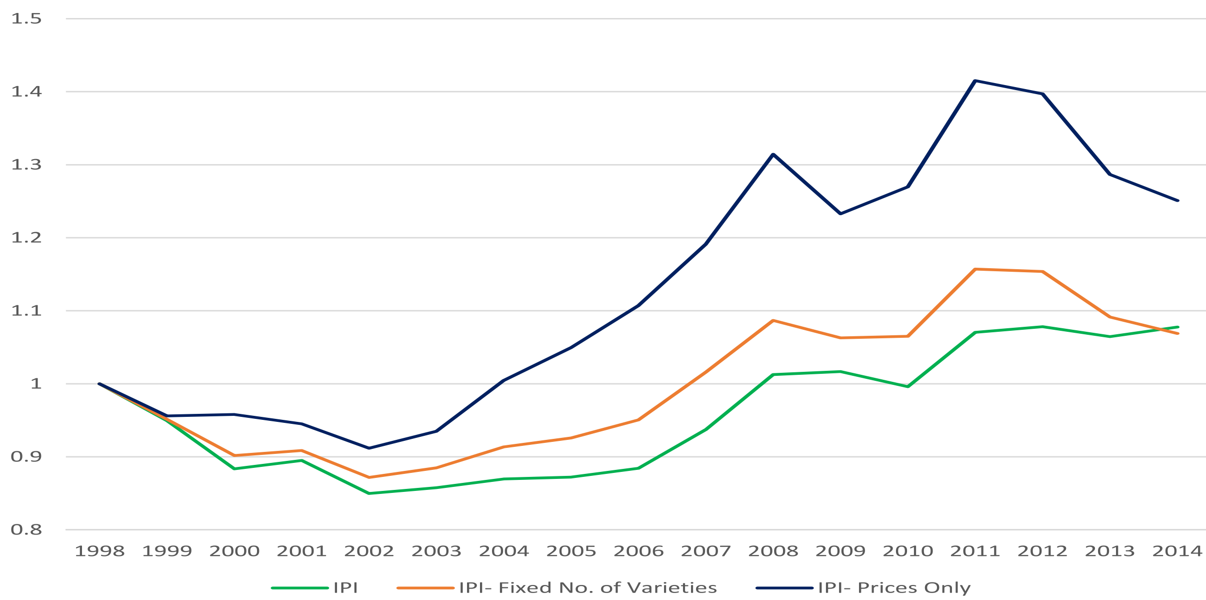
Figure 6 compares the geometric average of observed variety-level prices (the blue line), the first term of the price index breakdown in Equation 41, with our aggregate import price index (the green line). This geometric average of prices declined much less in the first half of the period than the overall index, while rising at a faster rate relative to the overall index in later years. In general, a widening gap between the two indicates that changes in the number of varieties or changes in dispersion in prices is causing the differences. Which mattered more? The orange line in Figure 6 illustrates the exercise of holding fixed the (average)

[41] For comparison, Broda and Weinstein (2006) use a CES aggregate import price index and find an upward bias in the non-variety-adjusted import price index of 28 percent, or 1.2 percentage points per year over the 1972-2001 time period. Relative to their exercise, our comparison to the Laspeyres price index includes additional sources of bias such as the substitution bias.

[42] Since our estimated α_v terms tend to be very small, the approximation of our price index by the CES-style component on the left side of Equation 41 is likely to be a very good one.

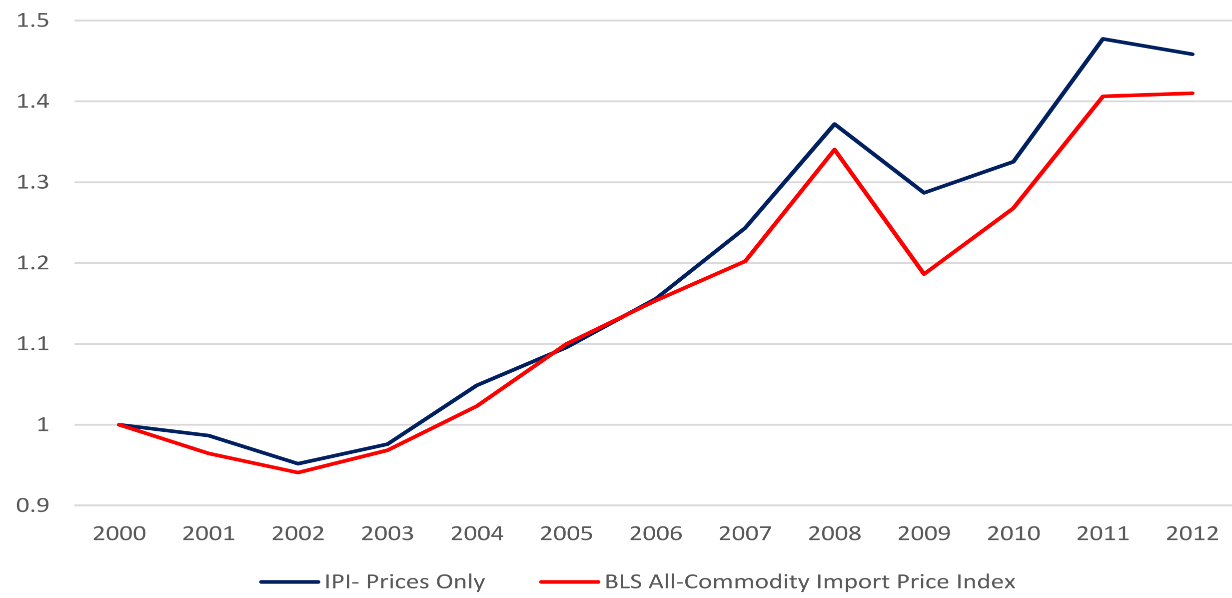
number of varieties in a sector at 1998 levels. Comparing the three lines makes clear that the increasing number of varieties did indeed lead to price index declines in the early part of the period. However, these effects are mostly washed out by the end of the period, meaning that in the end, changes in the number of available varieties did not affect prices much. Instead, changes in the *dispersion* of prices seem to matter much more for driving prices back up in the later half of the period, as the gap between the blue and green lines grows even as the gap between the blue and orange lines shrinks.

Figure 6: U.S. Import Price Index, Variants



Interesting, the geometric average of prices comes very close to the published BLS import price index. Figure 7 compares the geometric average price index (the blue line) with the price index from the BLS (the red line) over the 2000 to 2012 period, now setting 2000 to one for both series. Remarkably, the two price indices behave very similarly in this subperiod, with the exception that our price index falls significantly less in 2009 than the BLS price index.

Figure 7: U.S. Import Price Indexes, 2000-2012



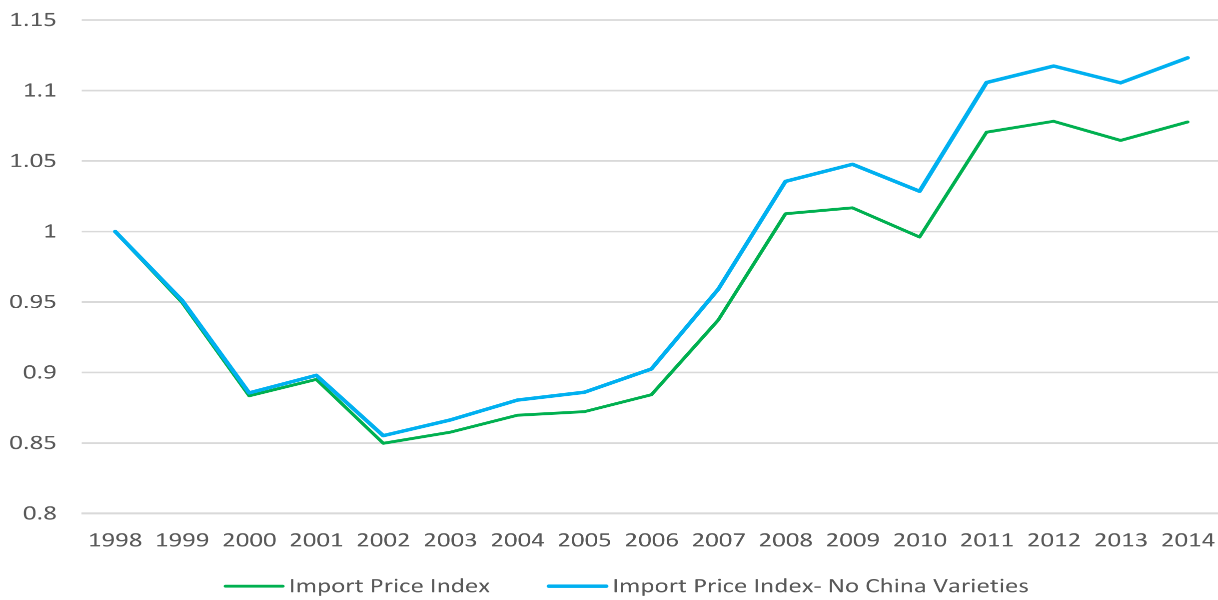
5.3.3 The Role of China

Another interesting question is the extent to which the well-known increase in U.S. trade with China contributed to changes in the aggregate price index. Although our model does not permit a full general equilibrium accounting of such an exercise, we can plot how the prices of non-Chinese varieties moved over this time period.[43] This comparison can be seen in Figure 8. Beginning in 2002, import price inflation for the group of non-Chinese varieties also rose more than the overall price index, implying a deflationary effect of China for U.S. consumers. According to our baseline index, overall import inflation was 0.47% annualized between 1998 and 2014, while the non-China index was 0.73% [44].

[43]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.

[44]When we look at the results of the same exercise focusing just on consumer products at the decile level, we will find a difference in annual average inflation rates of about 0.5 percentage point, which is twice as large as this aggregate result.

Figure 8: U.S. Import Price Index, With and Without Chinese Varieties



5.4 Import Price Inflation Across Consumers

5.4.1 Baseline Results

Figure 9 reports import price indices for selected income deciles over the entirety of 1998 through 2014, namely the lowest, median, and second-highest deciles of income in the United States.[45] The results for these and other deciles are reported in table form in the appendix. The dashed lines in the figure represent error bands, computed by recalculating the income-decile specific price indices using values of σ that represent the 95% thresholds for this parameter above.[46]

There are several features of Figure 9 to discuss. First, note that the price index for the ninth decile of income is below the other deciles in every year after 2002. Thus, the higher-income households experienced less cumulative import price inflation than other households. Second, with the exception of 2009, the price index for the lowest decile of income was above the other deciles in almost every year after 2002. Therefore, the lowest-income households experienced the most cumulative import price inflation over this time period.

[45] The U.S. Census Bureau does not disclose income amounts for the third, seventh, or tenth deciles.

[46] Error bands calculated using the 95% thresholds from the nonlinear estimates of the sector level parameters β_s^E and β_s^C are also extremely tight, and are available upon request.

Figure 9: U.S. Import Price Index, 1998-2014, Selected Income Deciles

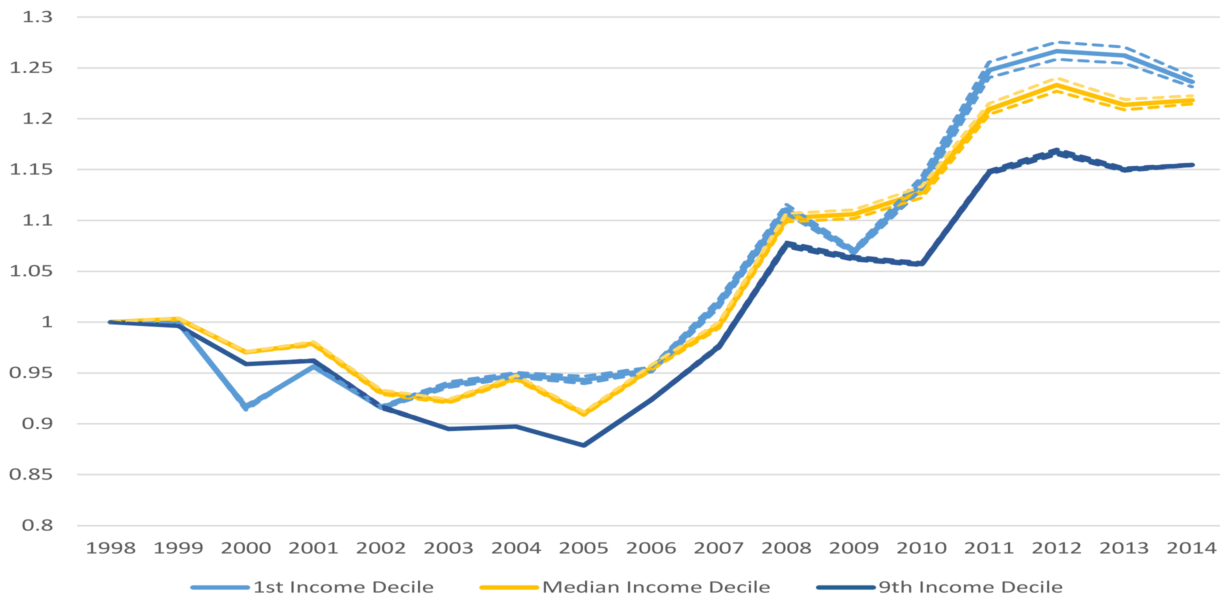


Figure 9 can be compared with changes in nominal income for different deciles over the same time period. As can be seen in Figure 10, U.S. Census data on income thresholds indicate that the lowest income needed to be included in the ninth income decile has risen about 7.5% from 1998 to 2014. At the same time, the lowest income of consumers needed to be included in the second decile has dropped by about 12.5% [47].

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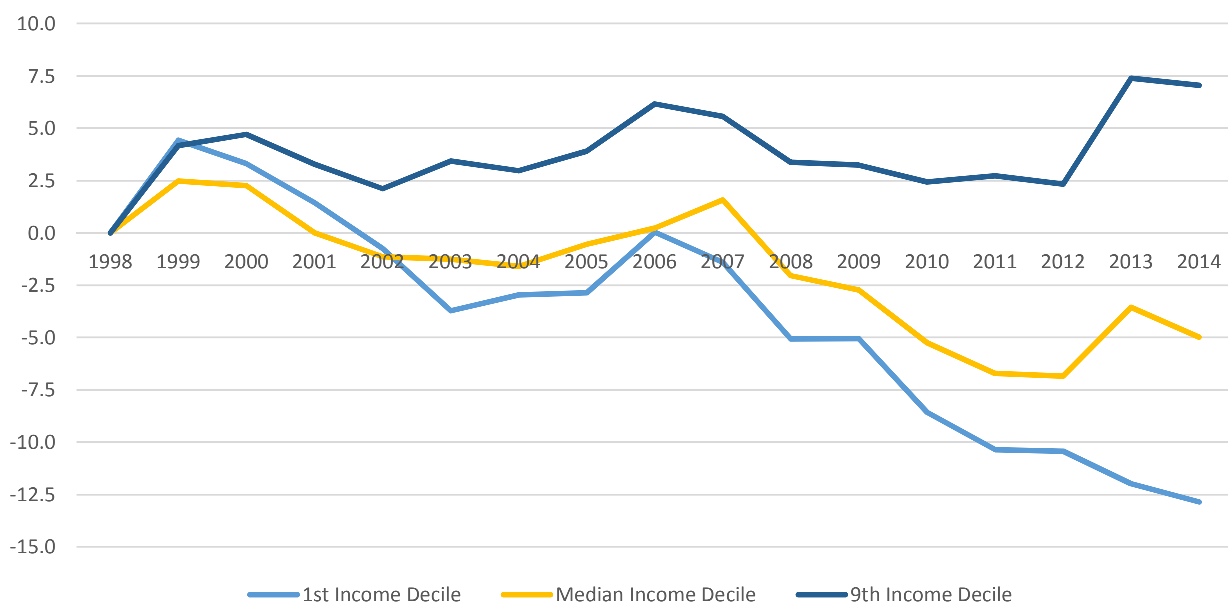
Figure 10: Cumulative Percent Change in U.S. Decile Income Thresholds, 1998-2014



[47] We report the full set of decile thresholds in Table 18 in the Appendix.

Figure 11 shows the average annual change in income thresholds by decile over the 1998 to 2014 period. Note that decile five is the median decile of income, and we do not report results for deciles three, seven, or ten. Notably, there is a positive relationship between the decile of income and its average annual income threshold change over this time period.

Figure 11: Average Annual Income Threshold Change by Decile, 1998-2014

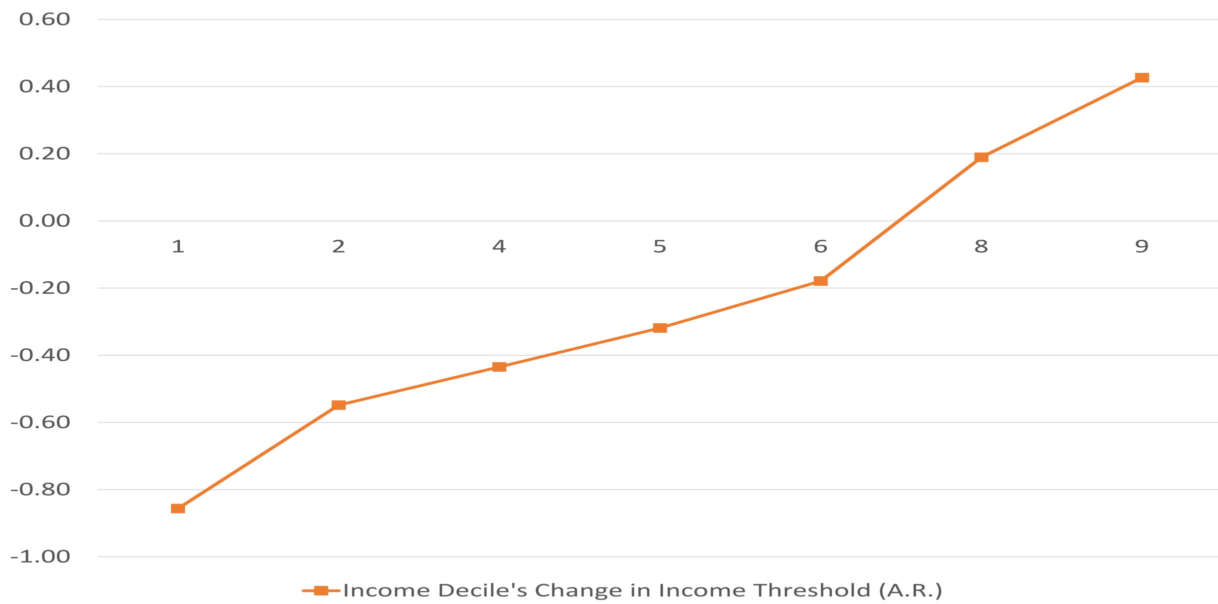
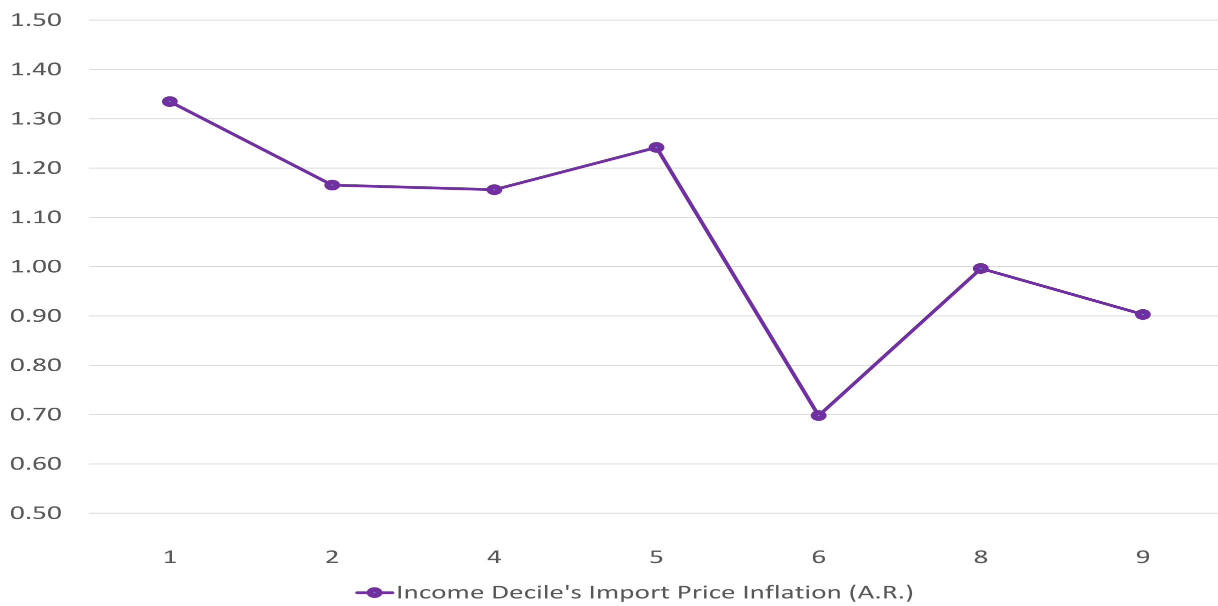


Figure 12 plots the import price inflation rates experienced by different deciles over the 1998 to 2014 period. We can see that the lowest-income households experienced the most inflation, while import price inflation was substantially lower for higher-income deciles. Therefore, we find a negative relationship between the decile of income and the average annual import price inflation over this time period. Importantly, the sign of this relationship is the opposite of what we saw in terms of nominal income changes. Thus, changes in import prices appear to be exacerbating increases in nominal income inequality over this time period.

Figure 12: Average Annual Import Price Inflation by Decile, 1998-2014

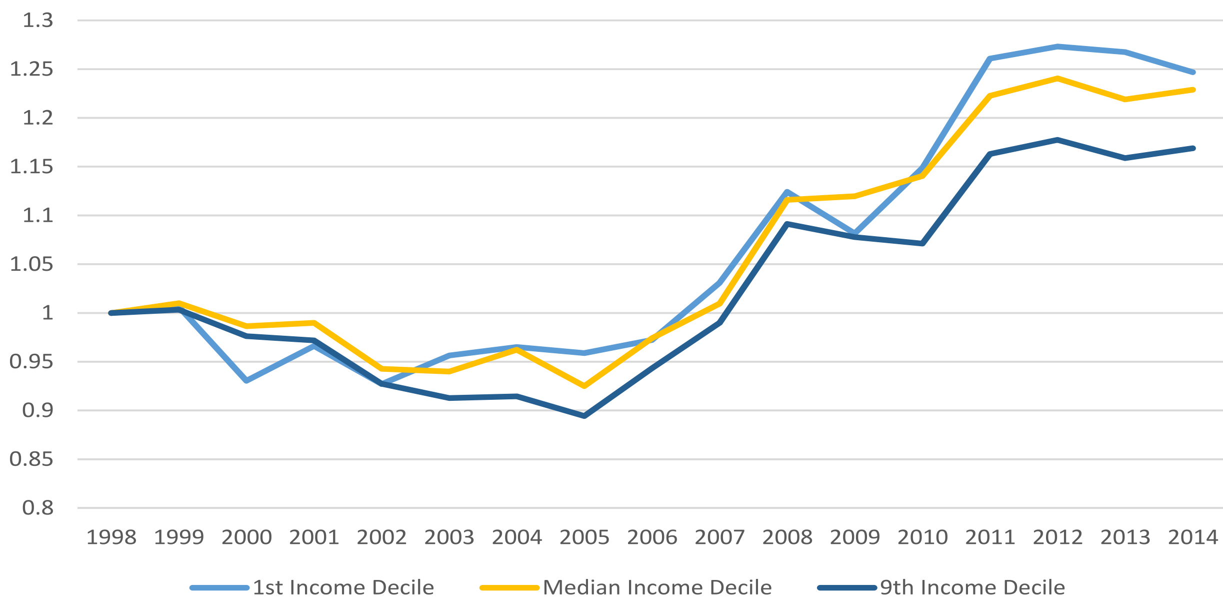


5.4.2 Within- vs. Across-Sector Non-Homotheticity

Our model permits both within-sector (through α_v) and across-sector non-homotheticity (through φ_{hst}). In this section, we consider the relative importance of each of these channels to the differences in decile-level import price inflation described above.

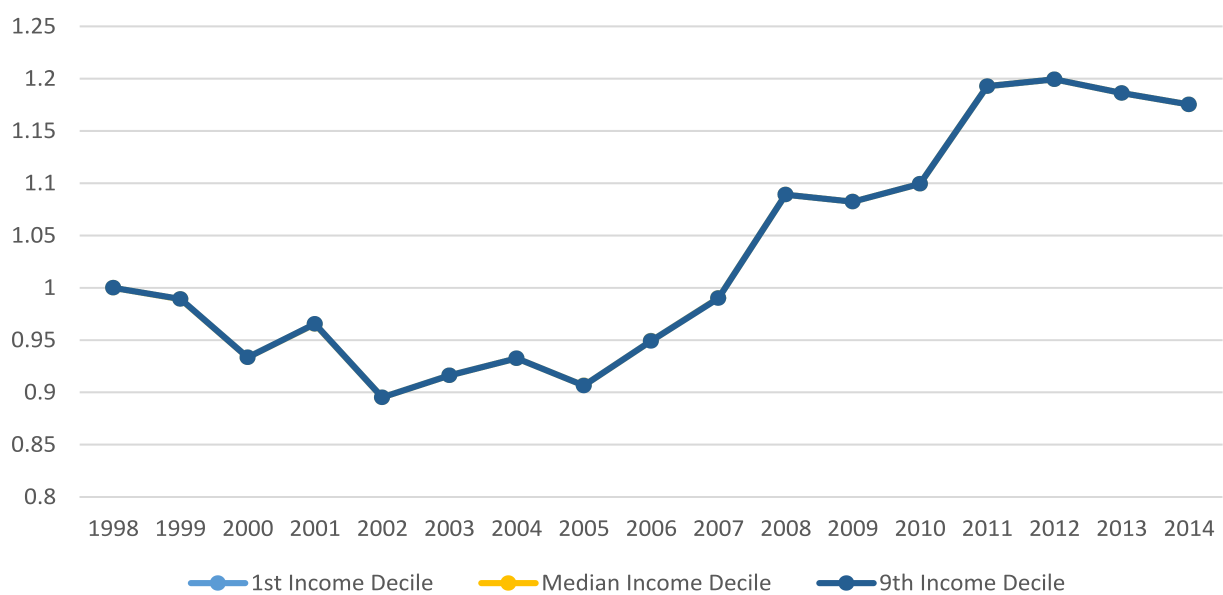
We first set all α_v terms equal to zero and recalculate the decile-level price indices. As can be seen from Figure 13, shutting down within-sector non-homotheticity changes the lines only slightly and does not alter the qualitative picture that consumers in the lowest income decile experienced the highest level of import price inflation.

Figure 13: U.S. Import Price Index for $\alpha_v = 0$, Selected Deciles



However, shutting down cross-sector non-homotheticity by setting all household-level sectoral demand shifters φ_{hst} equal to the sectoral average φ_{st} leads to a very different picture. Figure 14 shows that by shutting down variation in the sectoral demand shifters across households, import price inflation differences across deciles collapses to the point of being indistinguishable.[48]

Figure 14: U.S. Import Price Index for $\varphi_{hst} = \varphi_{st}$, Selected Deciles

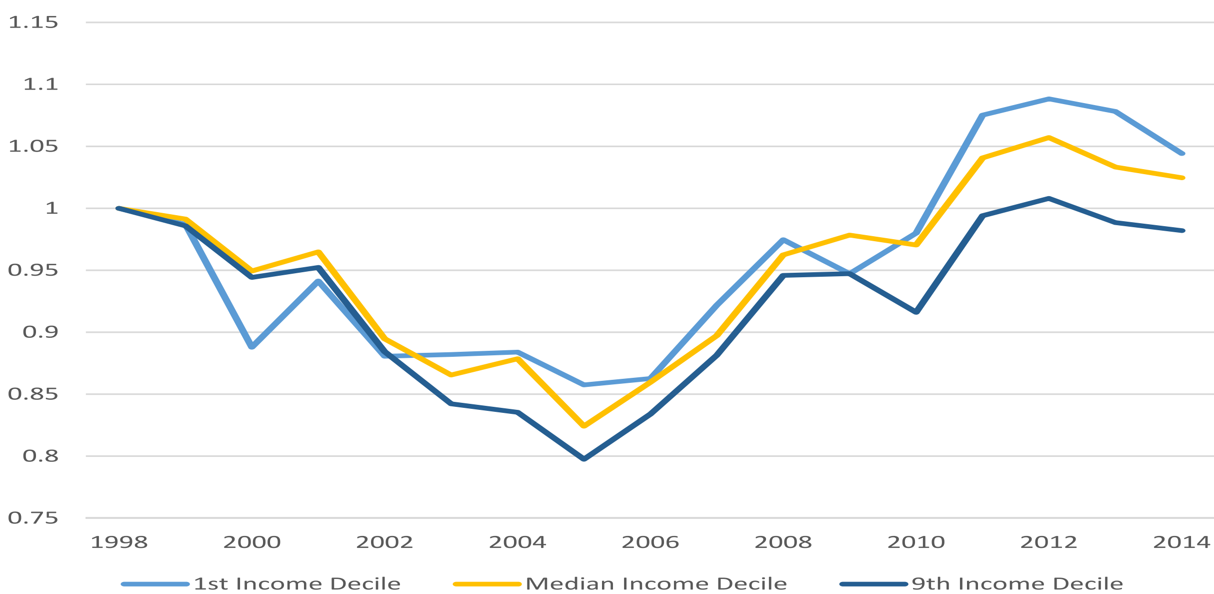


[48]Individual yearly observations of the index are not exactly equal; they tend to differ by about 0.0001 to 0.0002 percentage point.

5.4.3 The Role of Different Products

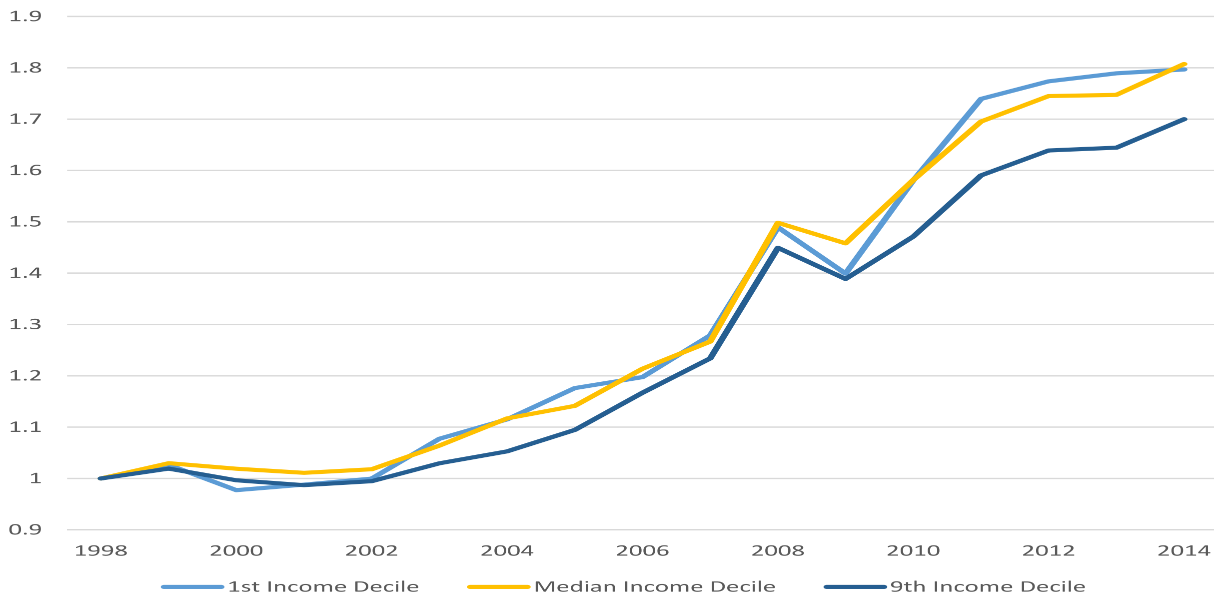
Although we have shown that the total share of income spent on imported products does not differ much across income deciles, it is still the case that the share of income spent on particular imported products differs widely across deciles. One particularly useful decomposition is separating out food and energy products from the overall price index to generate a "core" import price index. As can be seen in Figure 15, this index preserves many of the same features of the baseline index: a U-shaped pattern for prices, important differences between deciles, and the ninth decile of income facing the lowest level of import price inflation.

Figure 15: 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 16 looks very different. Although the richest decile still has the lowest level of inflation, prices for these imported products rose steadily over the time period. Additionally, there are less stark differences between the median and lowest-income deciles for non-core products.

Figure 16: U.S. Import Price Index for “Non-Core" Products, Various Deciles



5.4.4 Adjusting the Aggregate Elasticity of Substitution

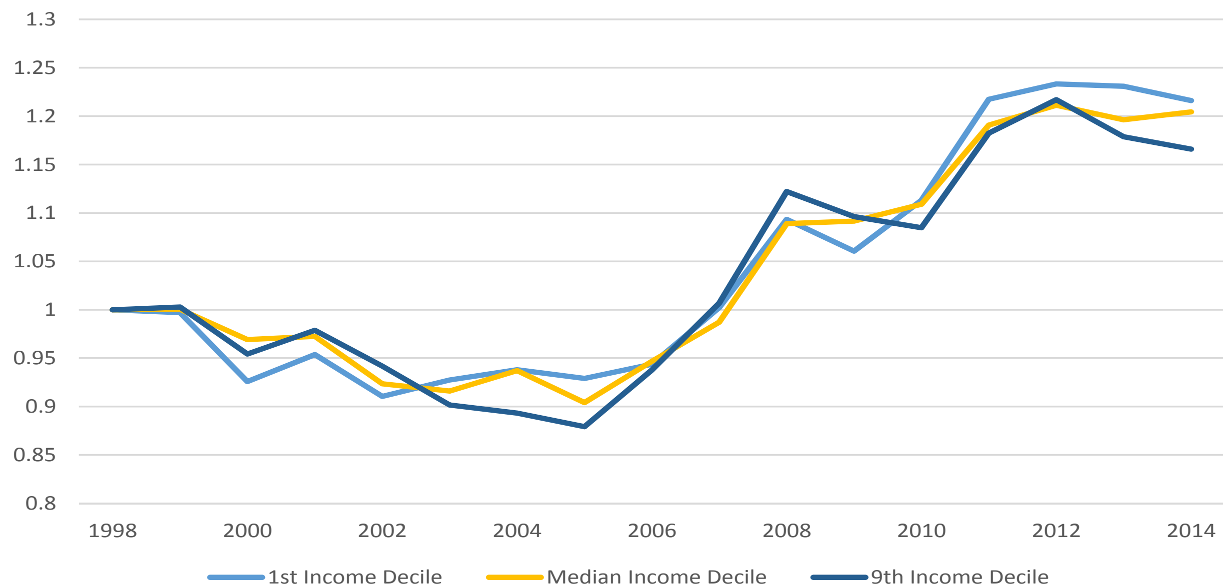
Recall from Section 4 that, using a properly instrumented version of the sectoral price index to trace out the demand curve, we estimate a value of the aggregate elasticity of substitution of 2.8. As a robustness check, we allow for different deciles to have different elasticities of substitution by estimating Equation 38 decile by decile. The implied σ_h coefficients are listed in Table 13. We find higher substitution elasticities for lower-income deciles.

Table 13: Decile Specific σ_h

Decile	1	2	4	5	6	8	9	Avg.
σ_h	3.26	3.11	3.02	3.18	2.49	2.66	1.93	2.81

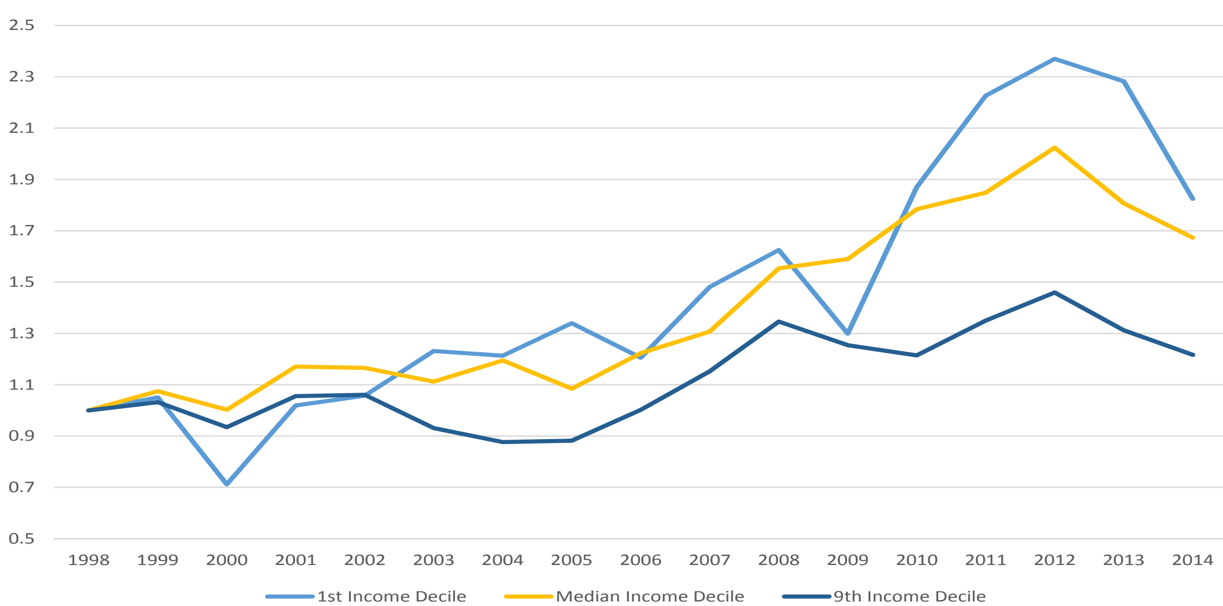
When we apply these decile-specific elasticities to the price indices (see Figure 17), we find some minor differences compared with our baseline results. The contour remains the same, but the differences between the lines are less pronounced.

Figure 17: U.S. Import Price Index, Decile-Specific σ_h



Our estimate of $\sigma = 2.8$ is higher than Redding and Weinstein (2017)'s estimate of 1.36, partly because our estimation sample for the second stage includes only those sectors that are directly consumed by households, as is clear from Equation 38. A typical parametrization of the aggregate elasticity of substitution in the literature would be $\sigma = 1$, which corresponds to Cobb-Douglas preferences. If we were to adopt a value of σ that is close to the estimate from Redding and Weinstein (2017) and much closer to Cobb-Douglas preferences, then our price index is changed significantly in magnitude relative to the baseline, as seen in Figure 18. Differences between income groups are far larger in this case.

Figure 18: U.S. Import Price Index, $\sigma = 1.3$



Essentially, higher levels of σ imply easier substitution across products for consumers and thus smaller levels of import price inflation. Combining this finding with our result that lower decile-specific σ_h values tend to be found for the highest-decile consumers means that differences in import price inflation could be partly explained by assuming the elasticity of substitution to be equal across consumers.

5.4.5 Import Price Inflation by Decile

Table 14 provides the annual average import price inflation rates experienced by each decile for the various exercises previously discussed. The results show a clear pattern, with the only exceptions being the case of non-core products and when we shut down across-sector non-homotheticity ($\varphi_{hst} = \varphi_{st}$), 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 14: Annual Average Import Price Inflation by Decile, 1998-2014

Decile	1	2	4	5	6	8	9
Baseline	1.33	1.17	1.16	1.24	0.70	1.00	0.90
$\alpha_v = 0$	1.39	1.22	1.22	1.30	0.74	1.06	0.98
$\varphi_{hst} = \varphi_{st}$	1.02	1.02	1.02	1.01	1.01	1.01	1.01
Without China	1.85	1.68	1.67	1.76	1.21	1.51	1.42
Core Products	0.27	0.11	0.05	0.15	-0.49	-0.08	-0.11
Non-core Products	3.73	3.45	3.62	3.77	3.72	3.55	3.37
$\sigma = 1.3$	3.83	2.80	2.75	3.27	0.01	1.79	1.23
Decile-specific σ_h	1.23	1.12	1.12	1.17	0.67	1.01	0.96

6 Conclusion

We estimate that developments in U.S. trade over the past two decades have had important distributional consequences through the consumption channel. In particular, we find 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. Therefore, we do not find evidence that the consumption channel has mitigated the distributional effects of trade that have occurred through the nominal income channel in the United States over the past two decades. Instead, our results imply that import price changes have exacerbated the increase in nominal income inequality.

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Appendix

6.1 Supplementary Tables

Table 15: Aggregate Import Price Index, 1998-2014

Year	Price Index
1998	1.0000
1999	0.9496
2000	0.8835
2001	0.8951
2002	0.8498
2003	0.8577
2004	0.8697
2005	0.8722
2006	0.8843
2007	0.9373
2008	1.0126
2009	1.0168
2010	0.9961
2011	1.0705
2012	1.0782
2013	1.0646
2014	1.0777

Table 16: Implied Expenditure by U.S. Decile of Income

Year	1st Decile	2nd Decile	4th Decile	5th Decile	6th Decile	8th Decile	9th Decile
1998	22,691.64	26,500.19	39,771.70	47,594.73	59,164.12	77,489.22	80,510.08
1999	23,484.90	28,776.54	41,779.38	49,057.11	60,734.75	80,188.73	83,908.75
2000	25,042.57	29,985.88	43,442.33	48,546.20	60,319.89	80,070.49	84,368.44
2001	23,826.67	28,081.95	41,022.47	48,034.21	60,286.87	79,535.57	83,257.29
2002	23,527.28	27,756.49	41,300.90	47,736.58	59,840.07	78,754.93	82,282.56
2003	21,845.63	27,262.87	39,284.88	47,137.25	59,253.98	79,648.11	83,368.51
2004	21,265.66	25,953.35	37,191.67	44,776.65	55,781.26	78,565.46	83,005.80
2005	21,051.07	26,469.51	39,363.39	46,600.36	58,002.03	79,215.77	83,784.38
2006	23,141.08	27,433.93	39,338.86	47,844.29	59,555.79	81,156.70	85,570.55
2007	22,580.07	27,648.00	41,167.83	48,591.39	59,974.48	81,331.92	85,086.75
2008	22,304.27	27,779.90	38,852.76	47,057.79	58,678.04	78,509.91	83,324.13
2009	23,087.09	26,666.13	37,624.56	45,531.39	56,529.72	78,620.31	83,237.56
2010	20,341.74	25,329.12	37,464.52	43,315.35	54,060.81	77,366.00	82,566.92
2011	19,924.30	25,996.75	36,564.68	44,453.20	55,447.76	76,165.12	82,830.47
2012	20,094.04	26,401.61	38,077.93	44,352.56	56,145.12	76,452.87	82,485.29
2013	20,766.97	27,872.19	39,062.89	46,662.36	58,518.59	79,799.83	86,552.40
2014	21,796.67	27,533.58	40,352.67	46,514.05	59,131.45	79,960.80	86,283.93

Table 17: Baseline Import Price Index by U.S. Decile of Income, 1998-2014

Year	1st Decile	2nd Decile	4th Decile	5th Decile	6th Decile	8th Decile	9th Decile
1998	1	1	1	1	1	1	1
1999	0.9991	0.9691	0.9902	1.0031	1.008	0.9992	0.9962
2000	0.9161	0.8999	0.9298	0.9703	0.9759	0.9651	0.9589
2001	0.9563	0.9461	0.9661	0.9789	0.9775	0.9653	0.962
2002	0.9161	0.9077	0.9123	0.9311	0.9288	0.9195	0.9164
2003	0.9383	0.8996	0.921	0.9222	0.9183	0.8991	0.895
2004	0.9478	0.9191	0.9411	0.9452	0.9473	0.9012	0.8972
2005	0.943	0.901	0.9006	0.9099	0.9142	0.8836	0.8787
2006	0.9532	0.9431	0.9605	0.9552	0.9588	0.9274	0.9237
2007	1.0184	0.9886	0.9877	0.9969	1.0041	0.9742	0.976
2008	1.111	1.0763	1.109	1.1025	1.106	1.081	1.0762
2009	1.0693	1.084	1.1128	1.106	1.1131	1.0661	1.0628
2010	1.1367	1.1023	1.1036	1.1276	1.1164	1.0647	1.057
2011	1.2477	1.1748	1.2152	1.2092	1.2035	1.1662	1.147
2012	1.2665	1.1916	1.2128	1.2332	1.2027	1.1833	1.1673
2013	1.2622	1.1803	1.2145	1.2136	1.177	1.1692	1.15
2014	1.2363	1.2037	1.2019	1.2183	1.1177	1.1719	1.1547

Table 18: Income Thresholds by U.S. Decile of Income

Year	1st Decile	2nd Decile	4th Decile	5th Decile	6th Decile	8th Decile	9th Decile
1998	14,281	23,727	44,768	57,248	71,163	110,418	149,137
1999	14,914	24,702	46,014	58,665	72,630	114,216	155,366
2000	14,754	24,985	46,009	58,544	72,742	114,000	156,153
2001	14,486	24,361	45,162	57,246	71,849	113,195	154,038
2002	14,173	23,911	44,545	56,599	70,950	112,127	152,293
2003	13,749	23,468	44,369	56,528	71,059	113,358	154,246
2004	13,857	23,489	44,059	56,332	70,177	111,818	153,576
2005	13,873	23,570	44,244	56,935	70,864	112,705	154,965
2006	14,285	23,850	44,967	57,379	71,425	115,508	158,325
2007	14,079	23,489	45,262	58,149	71,770	115,758	157,431
2008	13,557	23,089	43,476	56,076	69,924	111,744	154,172
2009	13,558	22,880	43,124	55,683	69,134	111,865	153,963
2010	13,057	22,017	41,832	54,245	67,702	110,116	152,772
2011	12,802	21,617	41,096	53,401	66,609	108,375	153,214
2012	12,791	21,533	41,568	53,331	67,511	108,818	152,623
2013	12,570	21,638	42,282	55,214	69,242	113,582	160,150
2014	12,445	21,728	41,754	54,398	69,153	113,811	159,652

6.2 Parameter Restriction for Interior Solution to UMP

As in Barnett (1977), we require for regular interior solutions to the utility maximization problem that

$$k_{hv} < \alpha_v < q_{hvt}, \tag{42}$$

where

$$k_{hv} = -\left(\frac{{p_{vt}}^{-\sigma^s}\varphi_{vt}^{\sigma^s-1}}{\sum_{k\in G_s}(\frac{p_{kt}}{\varphi_{kt}})^{1-\sigma^s}}\right)(Y_{hst} - \sum_{k\in G_s}\alpha_k p_{kt}). \tag{43}$$

Further, the regularity region is defined by the set of prices and income that satisfy

$$Y_{hst} > \sum_{v\in G_s}\alpha_v p_{vt}. \tag{44}$$