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Who's Most Exposed to International Shocks? Estimating Differences in Import Price Sensitivity across U.S. Demographic Groups*

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Abstract

Differences in consumption patterns across demographic groups mean that international price shocks differentially affect such groups. We construct import price indexes for U.S. consumer groups that vary by age, race, sex, education, and urban status. Black consumers and college graduates experienced significantly higher import price inflation from 1996-2018 compared to other groups, such as high school dropouts, rural consumers, and consumers over 60. Sensitivity to international price shocks varies widely, implying movements in exchange rates and foreign prices, both during our sample and during the Covid-19 pandemic, drove sizable differences in import price inflation – and total inflation– across groups.

JEL CLASSIFICATION: D12, E31, F31
KEYWORDS: import price inflation, exchange-rate passthrough, inequality

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1 Introduction

Movements in relative prices can lead to heterogeneous inflation rates across different types of consumers, as consumers can have different consumption baskets and consume goods in different proportions. International price movements, such as movements in exchange rates, are especially appealing for considering how heterogeneous inflation rates may arise, as they are plausibly exogenous from the point of view of a domestic consumer. Grouping consumers by their income is a common approach for work studying the role of international shocks in heterogeneous inflation: papers such as Cravino and Levchenko (2017)) and Auer et al. (2022) study how households of different income levels are affected by large currency devaluations or appreciations.[1] That said, grouping consumers by other demographic characteristics is also known to generate heterogeneous inflation rates– Black and Hispanic households in the United States have been shown to have higher inflation, for example– but the role of international price shocks in driving that heterogeneity is unknown.

In this paper, we measure the role of international price shocks in driving differences in inflation across a variety of demographic groups. To do so, we build import baskets from 1996 through 2018 for U.S. consumers that reflect differences in category weights by age, education, race, sex, and urban status. Using detailed prices from confidential U.S. import transactions data, we generate group-level import price indexes, and study whether the pass-through of movements in dollar and foreign producer price indexes into import prices differs by demographic group. Average import price inflation is about 1.9% per year, but differences in import price inflation are sizable, with Black consumers and college graduates featuring high inflation relative to rural consumers and high school dropouts. The sensitivity of these price indexes to international shocks also differs substantially by group: as one example, we estimate that dollar appreciation from 1996 through 2018 led to 9% lower import prices for White consumers compared to effectively no decline for Black consumers. Movements in international prices are thus not only a key component of differences in import price inflation between groups, but also, given that imports are about 10% of all expenditures, imply noteworthy differences in total CPI inflation as well.

Our starting point is to use microdata from the U.S. Consumer Expenditure Survey to determine how expenditure on imports varies across demographic characteristics. We compute expenditures at detailed product category levels for consumer characteristics within 5 demographic categories: Age, Education, Race, Sex, and Urban/Rural. Using this spending data together with information on the set of consumer-facing imports from Furman et al.

[1] As another example, papers such as Porto (2006), Fajgelbaum and Khandelwal (2016) and Borusyak and Jaravel (2017) study whether low or high income consumers benefit more from trade.

(2017) and national import penetration rates at the sectoral level produces estimates for import expenditure at the Harmonized System (HS) 6-digit product level for each demographic group over the years 1996 through 2018.

There are meaningful differences in expenditure on imports across demographic groups. Certain groups tend to always spend a higher fraction of total expenditure on imports relative to other groups throughout our time period. For example, consumers under age 30 consistently spend about 1 to 2 percentage points more on imports than consumers between 30 and 60, who in turn always spend about 1 to 2 percentage points more on imports than consumers over age 60. Considering the panel dimension of the data, the average demographic group increased its share of total expenditure on imports from about 8 percent to about 11 percent from 1996 to 2018. This increase stems mainly from rising import penetration rates at the product level over time, rather than from a shift in the composition of spending towards products that are more import-intensive.

In order to construct group-specific import price indexes, we use a nested Constant Elasticity of Substitution demand system with non-homotheticity as in Hottman and Monarch (2020). We estimate the key parameters of the model using quarterly U.S. Census data on the universe of prices and sales of foreign suppliers exporting individual HS10 products to the United States from 1996 through 2018, and use our data on expenditure shares across groups to build import price indexes.

The indexes we generate indicate sizable differences in the rate of import price inflation between demographic groups. For example, although we estimate average import price inflation to be about 1.9% per year from 1998 to 2016, Black consumers averaged 3.1% annual import price inflation and college graduates 2.2%, high levels relative to rural consumers (1.5%) and high school dropouts (0.6 percent). Since consumers tended to spend about 10 percent of their total expenditure on imports, a difference of 1 percentage point in import price inflation per year implies, to a first-order approximation, a difference of 0.1 percentage points in total CPI inflation per year.

We seek to explain these differences in import price inflation rates using two key measures of international shocks: the exchange value of the dollar and foreign producer price inflation. The results indicate that certain groups have an extremely high sensitivity to dollar movements, such as high school dropouts, Asian consumers, and White consumers. The import basket of Black consumers, on the other hand, is effectively unaffected by exchange rate movements. Since dollar appreciation leads to lower import prices, our estimates imply that the 20% dollar appreciation from 1996 through 2018 would be predicted to lead to 9.4% lower import prices (all else equal) for White consumers compared to no decline for Black consumers, indicating that dollar movements are one potential explanation for why Black consumers faced higher import prices. The differences in sensitivity are large enough to generate differences even in total CPI inflation space for different groups. A variance decomposition indicates that together, the dollar and foreign inflation explain well the differences in import price inflation rates we find. Thus movements in international prices are a key driver of differences in import price inflation between groups.

Finally, as an extension for the Covid-19 pandemic period, we use the estimated pass-through regression coefficients to evaluate the expected effects of international price shocks on inflation on different demographic groups during 2021–2022, when the dollar appreciated by 8.3% cumulatively and foreign producer prices rose by 13.1%. We find that this shock implies massive differences in import price inflation: Black consumers would have over 9.5 percentage points higher import price inflation than high school dropouts. Why are the differences so large? Since Black consumers have effectively zero dollar pass-through and very high pass-through of foreign producer prices, the pandemic period is especially challenging for Black consumers, but less challenging for groups with large exchange-rate pass-through coefficients. These results imply sizable differences in total CPI inflation rates across groups in the pandemic period that arise from differential sensitivity to international shocks.

Our paper contributes to a growing literature in international economics on distributional effects via the consumption channel, such as Neary (2004), Fajgelbaum et al. (2011), Simonovska (2015), Faber and Fally (2022), and Atkin et al. (2018). These papers typically study differences across income groups. We focus on other demographic characteristics that are less well studied.

Our work is also related to papers examining the effects of trade policy on different types of consumers. Gailes et al. (2018) study how the tariff burden differs across U.S. households of different incomes and consumers of different genders. Taylor and Dar (2015) also show that U.S. tariff rates are quite different for apparel products for men compared to products for women. Furman et al. (2017) demonstrate that tariffs are a regressive tax, hurting lower-income consumers more. In contrast, we examine how the import prices of different consumers relate to movements in exchange rates and foreign prices.

There has been additional work that, as we do, uses the Consumer Expenditure Survey to construct inflation measures for different U.S. demographic groups. For example, Avtar et al. (2022) find that Black and Hispanic consumers experienced higher total CPI inflation than average while Asian consumers experienced lower during the 2021–2022 period. Lee et al. (2021) and Lee et al. (2022) show that Black households faced somewhat higher inflation and significantly more volatile consumer prices than White households from 2004 to 2020, and that Black households were more likely to consume products with higher price volatility. Hobijn et al. (2009) construct measures of inflation that differ by age, education, and income using the Consumer Expenditure Survey from 1985 through 2005, and McGranahan and Paulson (2005) find that from 1981 through 2004, the variability of inflation is higher for vulnerable populations, such as Black consumers, the elderly, and Food Stamp recipients. These papers all combine data on group-specific expenditure shares with (typically BLS) data on measures of product-level inflation (at various levels of aggregation). We go beyond taking the weighted average of prices and estimate sector- and group-specific taste shocks and sector-specific elasticities of substiution using our disaggregated import price data from the U.S. Census. Relative to these papers, our work demonstrates differences in inflation between consumer groups, but additionally shows that international shocks– including movements in the dollar and foreign prices– are to some extent driving those differences.

Finally, we consider our group-specific exchange rate pass-through estimates to be empirical evidence of a new channel for the distributional effects and transmission of monetary policy, in addition to those considered in Auclert (2019) and McKay and Wolf (2023). Indeed, the recent work of Auclert et al. (2021) shows in a quantitative New Keynesian open economy model that consumption basket heterogeneity is important for the real income channel of exchange rates on aggregate consumption.

The rest of the paper is organized as follows. Section 2 describes our findings on import expenditure by demographic characteristic. Section 3 describes the price data and lays out the nested CES framework we use for constructing import price indexes. Section 4 discusses the implementation of the model, while Section 5 presents estimated results including the differences in import price inflation across groups and the implied sensitivity of each to international price movements. Section 6 concludes.

2 Import Expenditure by Demographic Group

2.1 Data Construction

The Consumer Expenditure Survey (CE) collects data on expenditures, income, and demographics in the United States, and are the data that underlie the U.S. Consumer Price Index. For our analysis, we use the Public Use Microdata (PUMD), which provides very disaggregated expenditure information for individual respondents (excluding information that could identify them). The PUMD also includes adjustments for information that is missing because respondents were unwilling or unable to provide it. Surveyed respondents provide their expenditure for various Universal Classification Code (UCC) products, of which there are a total of around 650-670, depending on the year.[2]

In what follows, mirroring the language of the BLS, we will refer to consumer *characteristics* as individual survey responses within a particular *demographic*. For example, for the demographic "Race of Member", the available characteristics in 2004 are White, Black, Native American, Asian, Pacific Islander, and Multi-Race.[3]

Using the PUMD, we compute UCC product-level expenditures for a host of different characteristic groups for the years 1996 - 2018, and, to line up with the trade data, match those products to HS6 categories using a concordance developed in Furman et al. (2017).[4] We augment the concordance by restricting to only those HS6 categories considered as "consumer goods" under the Broad Economic Categories (BEC) defined by the United Nations.[5] Since these are consumer-facing final goods, the number of HS6 products we obtain is between 440 and 600 depending on the year (out of around 5,000 HS6 products per year in aggregate import data). These matched HS6 products constitute about 31% of total U.S. imports. Finally, in order to estimate a group's import expenditure on a particular HS6 product, we multiply a demographic group's total spending in that HS6 in each year by the import penetration rate for that HS6 in each year, where an HS6 import penetration rate is that HS6's import share in domestic absorption (i.e., production minus exports plus imports) at the national level.[6] Annual import and export data at the HS6 level for the United States is freely available from the U.S. Census Bureau, while production data for the United States is available at the NAICS-5 level in the NBER-CES Manufacturing Database from Becker et al. (2013), which we then concord to HS6 codes.[7]

Our analysis focuses on 5 demographics in the CE, which are listed below along with the

[2]These reflect only those categories listed under "Food" or "Expenditure" in the CE hierarchical grouping file, not items listed as "Assets", gifts, or anything else. See `https://www.bls.gov/cex/pumd/stubs.zip` for the full list.

[3]The Dictionary for Interview and Diary Surveys has a complete list of all demographics in the CE, and is available at `https://www.bls.gov/cex/pumd/ce_pumd_interview_diary_dictionary.xlsx`.

[4]In cases where multiple HS6 categories map into a single UCC, we distribute expenditures using U.S. import spending on each HS6 as a guide.

[5]See `https://unstats.un.org/unsd/trade/classifications/bec.asp`. The HS6- BEC-Rev. 5 concordance (available here: `https://unstats.un.org/unsd/classifications/Econ/tables/HS2012-17-BEC5_08_Nov_2018.xlsx`) specifies whether the end-use category for any HS6 product is considered a "consumer good".

[6]Note that Feenstra and Weinstein (2017) call this denominator both "domestic absorption" and "apparent consumption".

[7]The HS6 category for gasoline/petroleum products changes multiple times over our time period. Due to its importance for consumer baskets, we ensure that this product remains in our sample by calculating the import penetration ratio for each category in each year, and then harmonize them into a single HS6 code for all years for concording to CE data.

14 individual characteristics we use and their share within the sample being used:

Table 1: Selected Demographic Characteristics in the Consumer Expenditure Survey

Demographic	Characteristic	Share of Observations (2018)
	Under Age 30	12
Age	Age 30-60	53
	Over Age 60	35
	High School Dropout	10
Education	High School Graduate	43
	College Graduate	33
	Post-Graduate	14
	White	84
Race	Black	11
	Asian & P.I.	6
Sex	Male	48
	Female	52
Urban/Rural	Urban	93
	Rural	7

Notes: This table summarizes the share of observations for a particular characteristic within the selected demographic group. For the *Race* demographic, not all possible characteristics were included- the observation share is computed for characteristics in the used sample. Shares may not sum to 100 due to rounding.

Note that these are not the only characteristics available for these demographics. However, since the PUMD is a survey, the data becomes less representative of the overall population if there are very few respondents.[8] We left out certain characteristics and combined certain other characteristics together for this reason.[9] We additionally prioritized having consistently-defined characteristics over the entire time frame of our analysis.[10] Finally, we note that these characteristics are self-reported: even though about 20% of the U.S. population lives in a rural area according to the official Census Bureau definition, much greater

[8]The BLS includes calibration weights in its CE Public Use Microdata for each consumer in order to be representative of the full CE sample.

[9]We did not include "American Indian" or "Mixed" as characteristics in the Race demographic due to low observation counts. We combined the "Asian" and "Pacific Islander" categories and also selected age ranges. The number of respondents underlying each characteristic we use is summarized in Appendix A, Table A.3.

[10]For example, a variable identifying whether a consumer is of Hispanic origin is present in the CE, but was not defined for the entire length of our sample.

than the share of consumers in the CE, respondents answer these survey questions according to their own understanding.[11]

2.2 Share of Total Expenditure on Imports

Before comparing expenditure across imported products, we first examine characteristic-level total expenditure on imports for different demographics. The first 3 columns of Table 2 shows these shares for each characteristic in 1996, 2007, and 2018.

Table 2: Share of Total Expenditure on Imports

Demographic	Characteristic	1996	2007	2018	Δ Import Share 1996-2018
Age	Under Age 30	9.6	10.7	12.3	2.7
	Age 30-60	7.8	8.5	11.0	3.2
	Over Age 60	6.4	7.2	9.2	2.8
Education	High School Dropout	6.9	8.1	11.0	4.1
	High School Graduate	8.0	8.1	10.3	2.3
	College Graduate	7.9	8.8	10.9	3.0
	Post-Graduate	7.5	8.8	10.5	3.0
Race	White	7.5	8.5	10.5	3.0
	Black	9.7	8.3	11.1	1.4
	Asian & P.I.	8.2	8.4	11.0	2.8
Sex	Male	7.4	8.3	10.4	3.0
	Female	8.4	8.7	10.8	2.4
Urban/Rural	Urban	7.8	8.5	10.6	2.8
	Rural	7.4	8.3	11.2	3.8

Notes: For each demographic characteristic, total expenditure on imports is computed by multiplying HS6-level import penetration rates by the average expenditure on HS6s concorded to UCC codes as in Furman et al. (2017). Average total expenditure for a characteristic includes all spending on all UCC codes under "Food" or "Expenditure" in the Consumer Expenditure Survey.

For any given time period, differences in the share of expenditure on imports across different gender, race, and education groups are not particularly large. However, differences are more noticeable between age groups – consumers under age 30 spend about 3 percentage

[11] See "What is Rural America": `https://www.census.gov/library/stories/2017/08/rural-america.html`.

points more on imports than consumers over age 60. These differences can also be seen in Figure 1: differences in import expenditure are starkest between different age groups, while individual characteristics within other demographics have much more similar spending shares.

Another message from Table 2 and Figure 1 is that, consistent with findings in earlier work, spending on imports increased steadily over this time period across all characteristics. As shown in the last column of Table 2, for almost every demographic group, spending on imports is about 2 to 4 percentage points higher in 2018 than in 1996. Black consumers had the smallest increase (1.4 percentage points) while consumers who did not finish high school had the largest increase (4.1 percentage points). There are two (non-exclusive) explanations for increased spending on imports over time: either consumers shifted expenditures toward goods that are import-intensive, or the goods themselves have increasing import penetration rates. In order to disentangle which channel is more important, we hold HS6-level import penetration rates fixed at 1996 levels, and recompute total spending on imports. Comparing the first and second columns of Table 3 shows that changes in product-level import penetration from 1996 to 2018 were the dominant force behind the increased spending on imports; indeed, if the only factor changing over this period was the composition of consumption baskets, the share of expenditure on imports would actually have fallen slightly for the typical characteristic.

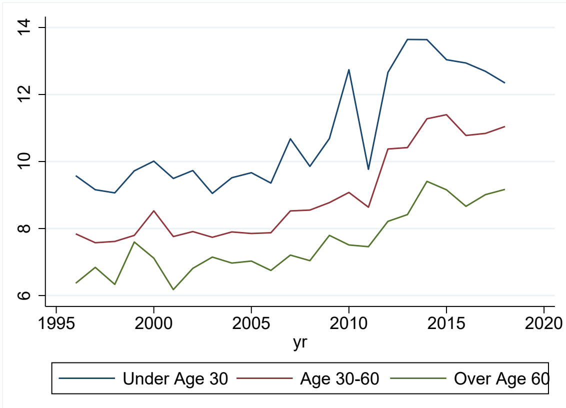
Table 3: Change in import expenditure Share (ppt.), 1996-2018

Demographic	Δ Import Share	Δ Import Share, using 1996 Import Penetration
Age	+2.9	-1.3
Urban/Rural	+3.3	-0.7
Education	+3.1	-1.1
Race	+2.4	-1.8
Sex	+2.7	-1.5

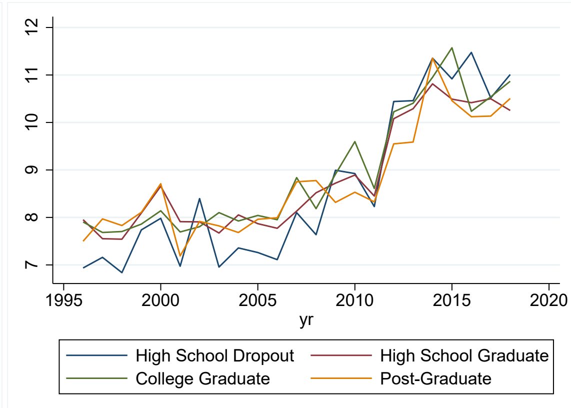
Notes: The above shows the simple average (across characteristics) change in the share of expenditure on imports for each demographic from 1996 to 2018, both in our full specification and by fixing import penetration shares at 1996 levels in 2018.

Figure 1: Share of Total Expenditure on Imports

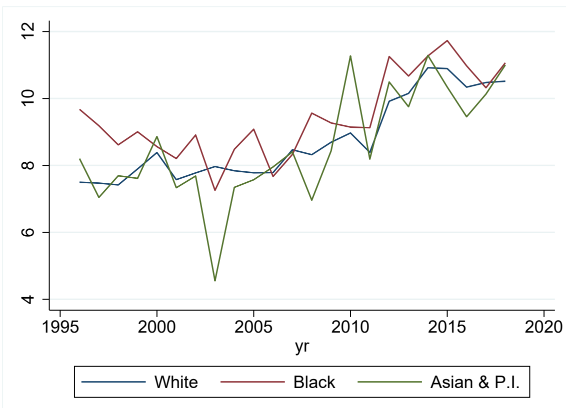
(a) Age



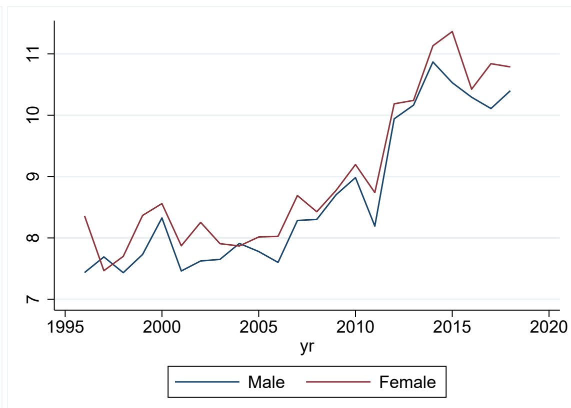
(b) Education



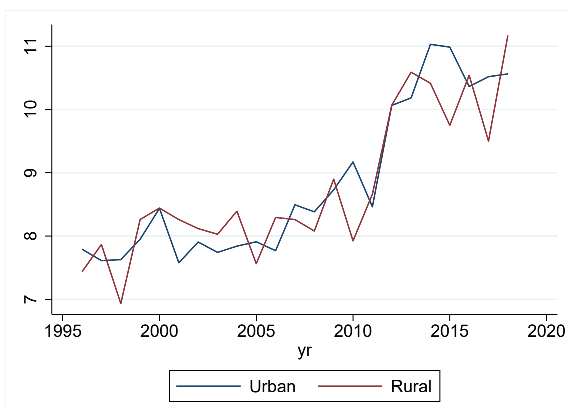
(c) Race



(d) Sex



(e) Urban/Rural



2.3 Product-Level Import Expenditures

We next turn to describing product-level import expenditure for different demographic characteristics. Recall that the expenditure data we construct consists of expenditure on imports of 450-600 HS6 products per year over 22 years for 14 different characteristics.

To start off, we illustrate which categories have the highest shares of import spending in 2018, by collapsing the data to the 2-digit HS level (of which there are around 50 per year). Table 4 lists the most purchased categories and their rank for each characteristic. The rankings are broadly similar, with consumption patterns dominated mainly by the same few imported categories: vehicles, apparel and footwear, and machinery and electronics. Averaging across characteristics, these 6 HS2 categories account for 58% of import expenditure, with HS2 87: Vehicles accounting for 17% of import expenditure.

Table 4: Rank of Highest Expenditure HS2 Categories, 2018

Demographic	Characteristic	87: Vehicles	61: Apparel, K	62: Apparel, NK	64: Footwear	85: Machines	84: Appliances
Age	< 30	1	2	3	4	9	7
	30-60	1	3	2	4	5	7
	> 60	1	2	3	4	6	7
Education	H.S. Dropout	1	2	3	4	9	5
	H.S. Grad.	1	2	3	4	6	5
	College Grad.	1	2	3	4	6	8
	Post-Grad	1	3	2	4	6	7
Race	White	1	2	3	4	5	7
	Black	1	3	2	4	7	5
	Asian & P.I.	1	2	3	4	5	6
Sex	Male	1	3	2	5	4	7
	Female	1	2	3	4	8	6
Urban	Urban	1	2	3	4	6	7
	Rural	1	2	3	5	8	10

Notes: This table lists the most-purchased HS2 expenditure categories, calculated by summing together import expenditure at the HS6 level, and their respective rankings for each demographic characteristic. "Apparel, K" refers to "Apparel and Clothing Accessories; Knitted or Crocheted", while "Apparel, NK" refers to "Apparel and Clothing Accessories; Not Knitted or Crocheted".

Recall from Figure 1 that there were noticeable differences in the overall import shares across age groups. We next use our HS6 expenditure data to identify the products that were the source of those differences. For example, recall that consumers under age 30 had a share of imports in total household expenditure that is about 3 percentage points higher than consumers over age 60 in the year 2018. Isolating the HS6 products that featured the biggest differences, this was due in part to the youngest consumers having 2 percentage points higher import expenditure in HS6 category 870323 (cars with engine cylinder capacity between 1500 and 3000cc), and another 1 percentage points higher spending in HS6 category 611120 (babies' garments) and HS6 950450 (video game consoles). Interestingly, even though the composition of the products explaining these differences change over time (in 1996, HS6 870324 drove higher spending among younger consumers), Figure 1 showed that younger consumers consistently had a larger share of spending on imports over time.

We can also investigate differences in import baskest composition across other groups. Higher import spending by rural compared with urban consumers in 2018 predominantly stems from higher spending on cars (870323, 870324). Partially offsetting this, urban consumers spent more on phones and accessories (851712), footwear (640399), and washing machines (845020). Though total spending on imports was similar for men and women, men spent about 1 percentage point more on phones and accessories, cars, and boy's/men's pants (851712, 870323, 870324, and 620342) each, while women spent about 1 percentage points more on women's shirts and tops (610610 and 610620). Relative to White consumers, Black consumers spent about 5 percentage points more on cars (870323), while white consumers spent 1 percentage point more on pet supplies (420100).

We now examine differential exposure of consumers to source countries. Table 5 shows the top 3 countries each consumer type was most exposed to in 1996 and 2018, along with the share of imports from that country. There are 2 main takeaways from Table 5. First, for the most part, the rankings of country-level exposure in a time period are very similar across consumer groups. The prime exceptions are the importance of Canada and Mexico for rural consumers in 2018. Secondly, the table shows that consumer purchases in 2018 were far more concentrated in a single source- with nearly 35% of purchases coming from China- relative to 1996. A similar point can be made for the importance of Mexico in U.S. consumption baskets, which typically occupied about 10% of import expenditure by 2018.

Table 5: Country-Specific Import Exposure by Characteristic

(a) 1996

Demographic	Characteristic	1st	2nd	3rd
	Under Age 30	China (17.1)	Canada (15.7)	Japan (10.9)
Age	Age 30-60	China (18.3)	Canada (13.9)	Japan (10.2)
	Over Age 60	China (17.6)	Canada (14.9)	Japan (11.1)
	High School Dropout	China (18.1)	Canada (15.0)	Japan (10.3)
Education	H.S. Grad.	China (17.6)	Canada (15.3)	Japan (11.2)
	College Graduate	China (18.4)	Canada (13.2)	Japan (9.6)
	Post-Graduate	China (18.5)	Canada (12.5)	Japan (9.4)
	White	China (17.4)	Canada (14.6)	Japan (10.6)
Race	Black	China (21.7)	Canada (13.2)	Japan (9.4)
	Asian & P.I.	China (19.1)	Canada (11.1)	Japan (8.6)
Sex	Male	China (17.7)	Canada (14.6)	Japan (10.4)
	Female	China (18.6)	Canada (13.8)	Japan (10.5)
Urban/Rural	Urban	China (18.1)	Canada (14.2)	Japan (10.3)
	Rural	China (17.3)	Canada (15.0)	Japan (11.2)

(b) 2018

Demographic	Characteristic	1st	2nd	3rd
	Under Age 30	China (37.2)	Mexico (8.4)	Vietnam (7.5)
Age	Age 30-60	China (37.1)	Mexico (9.0)	Vietnam (6.8)
	Over Age 60	China (35.6)	Mexico (9.0)	Canada (6.8)
	High School Dropout	China (34.6)	Mexico (10.0)	Vietnam (7.8)
Education	H.S. Grad.	China (36.5)	Mexico (8.9)	Vietnam (6.5)
	College Graduate	China (36.5)	Mexico (8.8)	Vietnam (6.6)
	Post-Graduate	China (38.5)	Mexico (8.8)	Vietnam (7.0)
	White	China (37.0)	Mexico (8.8)	Vietnam (6.5)
Race	Black	China (34.4)	Mexico (9.8)	Vietnam (7.3)
	Asian & P.I.	China (36.3)	Mexico (8.3)	Vietnam (8.2)
Sex	Male	China (36.0)	Mexico (9.1)	Vietnam (6.4)
	Female	China (37.5)	Mexico (8.7)	Vietnam (7.0)
Urban/Rural	Urban	China (37.0)	Mexico (8.9)	Vietnam (6.8)
	Rural	China (33.4)	Canada (9.2)	Mexico (8.4)

Notes: This table lists the top three sources of import expenditure for each characteristic, with the share of import expenditure from each country listed in parentheses.

Finally, we can extend the analysis from Tables 4 and 5 to see which countries were responsible for the most import-intensive products for each characteristic. Table 6 indicates that, other than for rural consumers, Japan was the most important source for Vehicles- HS2 87- while for most other major imported products, China was the most important source. Of note, some of these HS2 categories are particularly diffuse, explaining how Mexico and Vietnam are some of the top sources in 2018 without appearing in Table 5.

Table 6: Rank of Highest Expenditure HS2 Categories, 2018

Demographic	Characteristic	87: Vehicles	61: Apparel, K	62: Apparel, NK	64: Footwear	85: Machines	84: Appliances
	Under Age 30	JP	CH	CH	CH	CH	MX
Age	Age 30-60	JP	CH	CH	CH	CH	MX
	Over Age 60	JP	CH	CH	CH	CH	MX
	H.S. Dropout	JP	CH	CH	CH	CH	MX
Education	H.S. Grad.	JP	CH	CH	CH	CH	MX
	College Grad.	JP	CH	CH	CH	CH	MX
	Post-Grad	JP	CH	CH	CH	CH	MX
	White	JP	CH	CH	CH	CH	MX
Race	Black	JP	CH	CH	CH	CH	MX
	Asian & P.I.	JP	CH	CH	CH	CH	MX
Sex	Male	JP	CH	CH	CH	CH	MX
	Female	JP	CH	CH	CH	CH	MX
Urban/Rural	Urban	JP	CH	CH	CH	CH	MX
	Rural	CA	CH	CH	CH	CH	MX

Notes: This chart shows the main source of imports for the top HS2 categories for each demographic characteristic. "JP" represents Japan, "CA" represents Canada, "CH" represents China and "MX" represents Mexico. "Apparel, K" refers to "Apparel and Clothing Accessories; Knitted or Crocheted", while "Apparel, NK" refers to "Apparel and Clothing Accessories; Not Knitted or Crocheted".

With characteristic-level expenditure shares on HS6 products in hand, our next goal is to build import price indexes with these shares and import price data. We next lay out the framework we use to do this.

3 Price Data and Price Indices

3.1 Import Price Data

Throughout the empirical implementation of the model, we will consider a sector s to be an HS6 product imported by the United States, a variety v to be a foreign supplier-HS10 combination, and a group g to be one of the 14 demographic characteristics from the CE PUMD described in Section 2. We use quarterly U.S. import data for supplier-level prices and sales from 1996 through 2018.

In order to estimate the parameters of the model laid out below and generate import price indices, there are three main data requirements in our framework: prices, p_{vt} where v is a variety in sector s, group-level expenditure on sector s, Y_{gst}, and sales of variety v, $p_{vt}q_{vt}$. It is worth noting at this stage that the group-level expenditure data discussed in Section 2 is at an annual frequency though the sectoral price data is at a quarterly frequency. To generate quarterly group-level price indexes, we thus assume that the expenditure shares do not vary within a year. Since the group-level expenditure data was discussed in Section 2, this subsection briefly describes the data on trade prices and sales for each variety.

The international trade data come from the Linked-Longitudinal Firm Trade Transaction Database (LFTTD), which is collected by U.S. Customs and Border Protection and maintained by the U.S. Census Bureau. Every transaction in which a U.S. company imports a product requires the filing of Form 7501 with U.S. Customs and Border Protection, and the LFTTD contains the information from each of these forms[12]. There are typically close to 40 million transactions per year.

We use the import data from 1996Q1 to 2018Q4, which includes the quantity and value exchanged for each transaction, Harmonized System (HS) 10 product classification, date of import and export, country of origin, and a foreign supplier identifier. The foreign supplier identifier, known as the *manufacturing ID*, or *MID*, contains limited information on the name, address, and city of the foreign supplier[13]. Monarch (2022) and Kamal and Monarch (2018) find substantial support for the use of the MID as a reliable, unique identifier, both over time and in the cross section. A number of papers have used this supplier identifier, and in particular Redding and Weinstein (2017) show that many of the salient features associated with exporting activity (such as the prevalence of multi-product firms and high

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

[13]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.

rates of product and firm turnover) are replicated for MID-identified suppliers. Sales of a variety– a supplier-HS10 product pair– are simply the imported value associated with that variety, while prices are constructed as unit values, dividing variety-level value by quantity. These unit values are thus in the units of dollars per quantity. In the LFTTD, physical quantity units are specific to HS10 products[14].

3.2 Nested CES Preference Structure

In order to construct price indexes, we use data on prices, sales, and expenditures with a nested Constant Elasticity of Substitution demand system with non-homotheticity at the HS6 sectoral level. The structure of the model is similar to Hottman and Monarch (2020). However, as we will discuss there will be several important differences. One difference from that prior work (which was focused on income group differences using annual price data) is that we build our price indexes and estimate the parameters of our model using *quarterly* U.S. Census data on the universe of prices and sales of foreign suppliers exporting individual HS10 products to the United States.

Due to the fact that we are using over 20 years of quarterly data at the supplier-product level, we discipline the data by restricting our price estimation only to those supplier-product combinations that are available in a set of consecutive quarters. This ensures that small varieties that pass in and out from the data do not lead to outsize effects in the quarters they enter and exit, while still allowing for the the entry of new products into the consumption index over time. Thus we define $G_{s,t}$ to be the set of varieties in sector s at time t and $\overline{G}_{st} = \{G_{s,t+1} \cap G_{s,t} \cap G_{s,t-1}\} \cup \{G_{s,t} \cap G_{s,t-1} \cap G_{s,t-2}\}$ to be the set of varieties at time t that are a) also present in $t-1$ and b) present for at least 3 consecutive quarters (where t and $t-1$ are 2 of those quarters). We also define the set of tradable consumer goods sectors at time t to be S_t, with $\overline{S}_t = \{S_{t+1} \cap S_t \cap S_{t-1}\} \cup \{S_t \cap S_{t-1} \cap S_{t-2}\}$ the set of sectors at time t that are a) also present in $t-1$ and b) present for 3 consecutive quarters.

We assume U.S. consumers have ordinary CES preferences over sectors, such that the utility of group g at time t is given by

$$V_{gt} = \left[\sum_{s \in \overline{S}_t} \varphi_{gst}^{\frac{\sigma-1}{\sigma}} Q_{gst}^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}} \tag{1}$$

where V_{gt} is the CES aggregate of real consumption of tradable consumer goods sectors for group g at time t, Q_{gst} is the consumption index of sector s for group g at time t, $\varphi_{gst} > 0$ is a taste parameter for sector s for group g at time t, and $\sigma > 0$ is an elasticity parameter.

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

At the upper tier, non-homotheticity is generated from the sector-specific taste shifters at the group level, φ_{gst}.

The consumption index of sector s for group g at time t is

$$Q_{gst} = \left[\sum_{v \in \overline{G}_{s,t}} \varphi_{vt}^{\frac{\sigma^s - 1}{\sigma^s}} q_{gvt}^{\frac{\sigma^s - 1}{\sigma^s}} \right]^{\frac{\sigma^s}{\sigma^s - 1}} \tag{2}$$

where q_{gvt} is the real consumption of variety v in sector s for group g at time t, $\varphi_{vt} > 0$ is a demand shifter for variety v at time t, and $\sigma^s > 0$ is an elasticity parameter for sector s.

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

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

where Y_{gst} is the expenditure on sector s for group g at time t, and p_{vt} is the variety-specific price at time t, and P_{st} is a sectoral price aggregate given by

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

The utility maximizing expenditures of group g on sector s is:

$$Y_{gst} = \left(\frac{\varphi_{gst}^{\sigma - 1} {P_{st}}^{1-\sigma}}{P_{gt}^{1-\sigma}} \right) Y_{gt}, \tag{5}$$

where Y_{gt} is the total expenditure of group g at time t and P_{gt} is the group-level price aggregate. This equation shows that these preferences feature non-homotheticity at the sector-level, because we allow the sector-level taste shifters (φ_{gst}) to be different across income groups.

We have the following price aggregate for group g's imported consumption:

$$P_{gt} = \left(\sum_{s \in \overline{S}_t} \varphi_{gst}^{\sigma - 1} {P_{st}}^{1-\sigma} \right)^{\frac{1}{1-\sigma}} \tag{6}$$

As a technical matter, we form chained import price indexes first for any sector s by normalizing the first quarter of 1998 to a value of 100, and then taking cumulative products of the chain links, where the link for time t is given by

$$\frac{\mathcal{P}_{st}}{\mathcal{P}_{st-1}} = \frac{\left(\sum_{j\in\overline{G}_{s,t}} p_{jt}^{1-\sigma^s} {\varphi_{jt}}^{\sigma^s-1}\right)^{\frac{1}{1-\sigma^s}}}{\left(\sum_{j\in\overline{G}_{s,t}} p_{jt-1}^{1-\sigma^s} {\varphi_{jt-1}}^{\sigma^s-1}\right)^{\frac{1}{1-\sigma^s}}}. \tag{7}$$

We make the same normalization and use the same chaining procedure to form the group level price indexes, with the time t link given by

$$\frac{\mathcal{P}_{gt}}{\mathcal{P}_{gt-1}} = \frac{\left(\sum_{s\in\overline{S_t}} \varphi_{gst}^{\sigma-1} {\mathcal{P}_{st}}^{1-\sigma}\right)^{\frac{1}{1-\sigma}}}{\left(\sum_{s\in\overline{S_t}} \varphi_{gst-1}^{\sigma-1} {\mathcal{P}_{st-1}}^{1-\sigma}\right)^{\frac{1}{1-\sigma}}}. \tag{8}$$

In order to estimate a CES import price index for each group g in each period ($\mathcal{P}_{gt}$) as in Equation (8), we need a measure of the taste shifter φ_{gst}, an estimate of σ, and the sector level price indexes $\mathcal{P}_{st}$, which themselves require the variety-level taste shifter φ_{vt} and the sector-level elasticity of substitution σ^s.

In order to estimate these parameters, we close the model by assuming a basic monopolistic competition setting with decreasing returns to scale that gives the producer of variety v the following pricing equation:

$$p_{vt} = \frac{\sigma^s}{\sigma^s - 1}\delta_{vt}(1+\omega^s)q_{vt}^{\omega^s} \tag{9}$$

We can then implement the Feenstra (1994) estimation strategy, discussed next, to recover the key parameters of the model.

4 Implementation

In this section, we describe how we recover σ^s, ω^s, and φ_{vt}, addressing endogeneity concerns by applying the Feenstra (1994) approach of identification via heteroskedasticity to estimate the model.

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

Start from the variety-level demand expression in Equation 3. Taking logs, taking the time difference and differencing relative to another variety k in the same sector s gives

$$\Delta^{k,t}\ln(p_{vt}q_{vt}) = (1-\sigma^s)\Delta^{k,t}\ln(p_{vt}) + \nu_{vt}, \tag{10}$$

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

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

$$\Delta^{k,t} \ln p_{vt} = \frac{\omega^s}{1+\omega^s} \Delta^{k,t} \ln(p_{vt} q_{vt}) + \kappa_{vt}, \tag{11}$$

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

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

$$G(\beta_s) = \mathbb{E}_{\mathbb{T}} \left[x_{vt}(\beta_s)\right] = 0 \tag{12}$$

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

In words, we are assuming the orthogonality of the idiosyncratic demand (ν_{vt}) and supply (κ_{vt}) shocks at the variety level, after variety and sector-time fixed effects have been differenced out. The supply shock κ_{vt} is the residual of the pricing equation after accounting for fixed effects and the variation in prices due to movements along upward-sloping supply curves. The supply shock κ_{vt} thus represents shifts over time in the intercept of the variety-level supply curve- changes in price over time that occur for reasons other than changes in quantity sold. Our assumption is that these intercept shifts are uncorrelated with shifts over time in the intercept of the variety-level demand curve. This orthogonality assumption is more plausible in our setting using supplier-product trade data than in prior research using country-product trade data.

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

$$\hat{\beta}_s = \arg\min_{\beta_s} \left\{G^*(\beta_s)' W G^*(\beta_s)\right\} \tag{13}$$

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[15]. Following Broda and Weinstein (2006), we give more weight to varieties that are present in the data for longer time periods and sell larger quantities[16].

After obtaining ω^s and σ^s for each sector from the GMM estimation, we can recover the variety-level demand shifters. Although most papers in the literature on price index construction impose the assumption that variety-level quality is fixed over time, Redding and Weinstein (2020) show that the price index is still well-behaved so long as variety-level

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

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

quality is unchanged on average for the common set of varieties. Therefore, in this spirit, we normalize the geometric average of demand shifters in each sector (i.e., $\widetilde{\varphi_{kt}} = \widetilde{\varphi_k}$ across varieties in each sector, where the tilde denotes the geometric average). Then, the demand shifter for each variety can be computed differencing Equation 3 relative to the geometric average to get the following expression

$$\varphi_{vt} = \exp\left[\frac{\ln(p_{vt}q_{vt}) - \ln(\widetilde{p_{kt}q_{kt}}) + (\sigma^s - 1)(\ln p_{vt} - \ln \widetilde{p_{kt}})}{\sigma^s - 1}\right], \tag{14}$$

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

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

$$\Delta^{k,t}\ln(Y_{gst}) = (1-\sigma)\Delta^{k,t}\ln(P_{st}) + \upsilon_{gst}, \tag{15}$$

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

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

$$\Delta^{k,t}\ln P_{st} = \Delta^{k,t}\left(\frac{1}{N^v_{st}}\sum_{v\in\overline{G}_{s,t}}\ln p_{vt}\right) - \Delta^{k,t}\frac{1}{\sigma^S - 1}\ln\left(\frac{1}{N^v_{st}}\sum_{v\in\overline{G}_{s,t}}\frac{\left(\frac{p_{vt}}{\varphi_{vt}}\right)^{1-\sigma^S}}{\widetilde{\left(\frac{p_{vt}}{\varphi_{vt}}\right)^{1-\sigma^S}}}\right), \tag{16}$$

where N^v_{st} is the number of varieties in $\overline{G}_{s,t}$. We use the second 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

15. We use this term because the first term on the right-hand side is likely correlated with changes in the sector-level demand shifter, as average prices rise in response to positive sector demand shocks. Our identifying assumption for the instrumental variables regression is that the changes in dispersion in quality-adjusted prices within a sector are uncorrelated with the changes in the sector-level demand shifter φ_{gst}. Based on that assumption, we estimate Equation 15 using two-stage least squares to obtain an estimate of σ.

Given an estimate of σ, we can then finally generate the group-specific sectoral demand shifters (φ_{gst}) using our data on group-level expenditure described in Section 2. Along the lines of the above calculation of φ_{vt}, this can be done by normalizing $\widetilde{\varphi_{hkt}} = \widetilde{\varphi_{hk}}$ to the geometric average of the shifter for the common set across sectors and using Equation 5 in differences to derive

$$\varphi_{gst} = \exp\left[\frac{\ln(Y_{gst}) - \ln(\widetilde{Y_{gkt}}) + (\sigma - 1)(\ln P_{st} - \ln \widetilde{P_{kt}})}{(\sigma - 1)}\right] \tag{17}$$

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

5 Results

5.1 Elasticities of Substitution

The first empirical results to discuss are the estimated elasticities of substitution (σ^s), which are key parameters in the nested CES price indexes. We find a mean elasticity of 4.2, with a standard deviation of 2.8. These estimates are quantitatively similar to those reported in Hottman and Monarch (2020), and that paper further shows that its estimates are comparable to benchmark estimates from the literature.

Table 7 reports estimates of the elasticity of substitution across sectors. The OLS estimate of this parameter is 1.1, while our IV approach yields a point estimate centered at 1.78 with a 95 percent confidence interval between 1.75 and 1.81. These estimates are quite similar to those in Hottman and Monarch (2020), although higher than the elasticity of 1.36 reported by Redding and Weinstein (2017). Given this elasticity of substitution across sectors, we can solve for group-specific sectoral demand shifters (φ_{gst}) as in equation 17, allowing the computation of import price indexes across groups.

Table 7: Summary of σ

OLS	IV	95% Confidence Interval
1.09	1.78	$[1.75, 1.81]$

5.2 Group-Level Import Price Indexes

We now summarize the group specific import price indexes that result from our data, given our parameter estimates. We first show the average annual import price inflation rate $\bar{\pi}$ for each demographic characteristic group implied by our price indexes in Table 8.[17]

Table 8: Average Annual Import Price Inflation, 1996 Q1 to 2018 Q4 (%)

Characteristic	$\bar{\pi}$	Characteristic	$\bar{\pi}$	Characteristic	$\bar{\pi}$
High School Dropout	0.63	White	1.85	Under Age 30	2.16
High School Graduate	1.59	Black	3.14	Age 30-60	2.10
College Graduate	2.25	Asian & P.I.	1.92	Over Age 60	1.55
Post-Graduate	2.10				
College - H.S. Dropout	1.62	Black - White	1.28	Under 30 - Over 60	0.61

Characteristic	$\bar{\pi}$	Characteristic	$\bar{\pi}$
Urban	2.08	Men	2.05
Rural	1.46	Women	2.18
Urban - Rural	0.61	Women - Men	0.13

As shown in the table, there is significant heterogeneity both within and across groups: while the across-group average annual rate of import price inflation was 1.9% per year, consumers that are high school dropouts had the lowest rate at 0.6% per year, while Black consumers had the highest rate at 3.1% per year. Differences in average import price inflation between men and women are fairly small, while differences between characteristic groups in "Education" and "Race" exceed 1 percentage point per year. As we saw in Table 2, consumers in both of these latter categories spend about 11% of total expenditure on imports in 2018, which means that to a first-order approximation these differences would imply a

[17] Since we have 92 quarters in our data, average annual rates from 1996Q1 to 2018Q4 are calculated using the formula $\bar{\pi} = \left[\left(\frac{P_{2018Q4}}{P_{1996Q1}}\right)^{\frac{4}{91}} - 1\right] \cdot 100$.

difference of over 0.1 percentage points on *total CPI inflation* per year. Along the same lines, since consumers under age 30 spend 12% of total expenditure on total imports in 2018 and consumers over age 60 only 9%, the difference in import price inflation between these groups also implies a difference in *total CPI inflation* of over 0.1 percentage points per year (0.26 vs. 0.14). These are meaningful differences in inflation given that national CPI inflation was about 2.16 percent annually from 1996 to 2018.[18]

Where do these differences come from? In Section 2, we described how the consumption patterns of particular characteristic groups on various products differed from each other, which ultimately gives rise to import price differences. In terms of an economic explanation though, we conjecture that these import price inflation differences may be explained by a differential sensitivity of import baskets to determinants of import prices, such as the marginal costs of foreign production and the exchange value of the dollar. We examine this possibility next.

5.3 Additional International Price Data

With our group-specific import price indexes constructed, we study how different demographic groups are affected by movements in international prices, particularly the exchange value of the dollar and the rate of foreign producer price inflation in local currency terms. This subsection briefly describes how these latter data series are constructed.

Measures of the broad dollar are constructed using U.S. import weights for a variety of important trading partners and their respective bilateral exchange rates against the dollar.[19] However, since the import price indexes we generated consist only of consumer-facing products found in the CE, we also generate a version of the dollar that reflects such imports. In particular, we again use the concordance developed by Furman et al. (2017) between HS6 categories and UCC product codes to identify consumer-facing HS6 categories that are also identified by the BEC as consumer facing, and construct weights by source country based on that subset of U.S. imports, rather than all U.S. imports. We then use these weights to aggregate quarterly bilateral exchange rates, which are obtained from the IMF International Financial Statistics.[20] This would mean, for example, that if a certain source country exported mostly intermediate inputs to the United States, movements in its bilateral exchange rate would be less important in our index relative to its counterpart based on overall U.S.

[18]Although not shown, we also find that the differences in inflation between characteristic groups are persistent, and not very sensitive to the specific time period over which we compare groups.

[19]For example, the Federal Reserve publishes foreign exchange rates and the U.S. broad dollar index weekly in the H.10 tables, `https://www.federalreserve.gov/releases/h10/current/`.

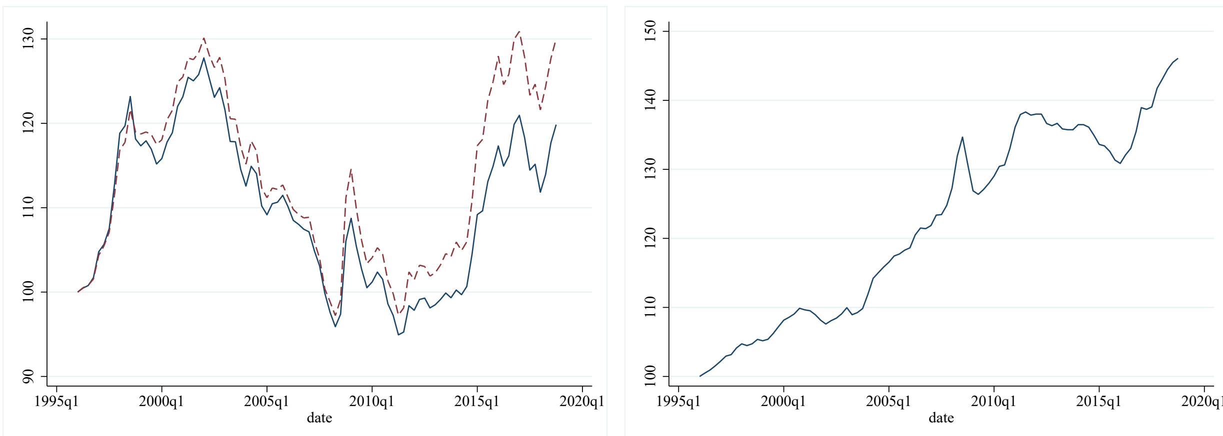
[20]The exact procedure is outlined in Appendix A.

imports. Panel A of Figure 2 shows the broad dollar indexes indexed to 1996 Q1, including both our consumer-import restricted version (blue solid line) and the version using all U.S. imported products (red dashed line). Although the series track each other fairly closely, from late 1998 onward, the level of the consumer-facing broad dollar is always lower. The differences between the series are also greater in the later part of the period. Interestingly, the version based only on consumer imports features about one-third less appreciation from 2011 through 2016. Over our whole sample period though, the consumer-facing broad dollar appreciated about 20% cumulatively, or about 0.8 percent per year.

Figure 2: International Prices

(a) U.S. Broad Dollar Index

(b) Foreign Producer Price Index



Notes: Panel (a) presents the broad real dollar index, where bilateral exchange rates are weighted by country shares within the set of consumer products found in the Consumer Expenditure Survey (blue solid line) as well as by overall U.S. import rates (red dashed line). Panel (b) presents a trade-weighted foreign producer price index, where individual country (manufacturing) producer price indexes are weighted by country trade shares within the set of consumer products found in the Consumer Expenditure Survey.

Consumers with different demographic characteristics could also be affected differently by movements in foreign prices. Increases in foreign producer prices, for example, naturally imply higher import prices for U.S. consumers. We thus include foreign producer price inflation as another potential reason for differences in import price inflation over this time period. Our data on producer price inflation comes from measures provided by individual countries. Where available, we use manufacturing producer price indexes. Just as with the construction of our dollar index, we use consumer-product trade weights to aggregate these producer price indexes across countries. Figure 2 Panel B shows the trend in the trade-weighted foreign producer price index for our time period: prices rose over the whole time period, with the index in 2018Q4 about 46% higher than in 1996Q1 (which is an annual rate increase of 1.7 percent per year).

5.4 Effects of International Prices on Consumer Groups

Pooling the quarterly import price data from 1996 Q1 through 2018 Q4 for our demographic groups, we specify the following regression equation:

$$\ln \mathcal{P}_{gt} = \beta_D \ln DollarIndex_t \times I_g + \beta_F \ln ForeignPPI_t \times I_g \qquad (18)$$
$$+ f_{quarter} + f_{year} + f_g + \varepsilon_{gt}$$

where $\mathcal{P}_{gt}$ is demographic group g's import price index in date t, the dollar index and the foreign PPI index are from section 5.3 above, I_g is an indicator for demographic characteristic group g, and quarter, year, and group fixed effects are also included. The β terms capture the long-run sensitivity of group import price indexes to each international price index. Including year fixed effects in the regression controls for common shocks at the annual frequency, while the quarter fixed effects adjust for quarterly seasonality. The regression contains 1,288 observations, and an R^2 of 0.87. To save space, we report only the relevant coefficients for each interaction term and its significance level below.

Table 9 reports the estimated coefficients on the dollar index, with statistical significance indicated by the level of stars. As would be expected, all the coefficients are either negative or not statistically significant from zero, indicating that dollar appreciation leads to lower import prices, as dollars buy more foreign currency and thus lower the dollar price that U.S. importers pay for items bought from other countries. The coefficients range from -0.7 for consumers who are high school dropouts to approximately 0 for Black consumers. Thus, we find that the import basket of high school dropouts had much greater sensitivity to the dollar relative to the basket of goods of Black consumers. The average of the coefficients is around -0.4. For rough comparison, Campa and Goldberg (2005) use quarterly data from 1975 through 2003 and estimate exchange rate coefficients into U.S. import prices for different sectors and horizons of between -0.114 and -0.604, with coefficients for aggregate import prices in the short-run of -0.23 and in the long-run of -0.42. Using a more recent data sample from 1994-2005, Gopinath et al. (2010) estimate exchange rate pass-through into aggregate U.S. import prices of -0.32 (conditional on a price change) and -0.54 (for lifelong pass-through). Burstein and Gopinath (2014) use data from 1985-2011 and estimate short-run pass-through into U.S. import prices of -0.2 and long-run pass-through up to -0.51. A final comparison is to the United Stations International Transactions (USIT) model used by Federal Reserve staff to understand movements in core import prices: the model estimate using data from 1990 through 2013 is that dollar pass-through over two quarters is -0.24.[21] Thus our dollar pass-through estimates are broadly in line with other work in the literature.

Table 9: Dollar Pass-Through

Characteristic	Dollar Pass-Through (β_D)
High School Dropout	-0.70***
Asian & P.I.	-0.52***
H.S. Grad.	-0.48***
White	-0.47***
Urban	-0.44***
Over Age 60	-0.42***
Male	-0.39***
Post-Graduate	-0.37***
Age 30-60	-0.36***
College Graduate	-0.33***
Rural	-0.33**
Female	-0.31***
Under Age 30	-0.29**
Black	0.06

Notes: Group-specific pass-through estimates from Equation (18). *** implies that the estimates are different from zero at the 99% level, ** at the 95% level and * at the 90% level.

From 1996 through 2018, as shown in Figure 2, our consumer-product dollar index cumulatively appreciated 20%. Our dollar coefficients imply that, all else equal, this dollar appreciation would be expected to result in import prices for high school dropouts to decline by 14% (0.20 $\times$ -0.70) cumulatively. As another example, considering the significantly higher import price inflation faced by Black consumers relative to White consumers highlighted above, dollar appreciation over the sample period would have implied an import price decline of 9.4% for White consumers and very little decline for Black consumers. Thus movements in the dollar are one potential explanation for why Black consumers faced higher prices.

We next summarize the results on foreign producer price inflation pass-through. The results are shown in Table 10. In this case, the coefficients flip from negative to positive; this is intuitive, as higher foreign inflation should lead to higher import pries. The average rate of pass-through from foreign inflation across groups is about 0.47. By way of comparison,

[21] See Gruber et al. (2016), "Core Import Prices" Equation, coefficients on s_t and s_{t-1}.

the USIT model used by Federal Reserve staff estimates the pass-through coefficient from foreign inflation to be 0.49.[22] We again see differences between characteristics in their import price sensitivity to foreign inflation. Black consumers have very high pass-through, with a coefficient of about 0.9. However, high school dropouts and rural consumers have pass-through coefficients that are close to zero.

Table 10: Foreign Inflation Pass-Through

Characteristic	Foreign PPI Pass-Through (β_F)
Black	0.87***
Under Age 30	0.71***
Female	0.66**
Asian & P.I.	0.64**
College Graduate	0.63**
Post-Graduate	0.55*
Urban	0.51*
Age 30-60	0.51*
White	0.48*
Male	0.40
Over Age 60	0.33
H.S. Grad.	0.28
Rural	0.04
High School Dropout	0.01

Notes: Group-specific pass-through estimates from Equation (18). *** implies that the estimates are different from zero at the 99% level, ** at the 95% level and * at the 90% level.

5.5 How Much of the Across-group Variance in Import Price Inflation is Explained by Model Factors?

We next assess how much of the variation in group-specific import price inflation is explained by the covariates we used above, namely the exchange rate and foreign PPI inflation. To do this, we compare our group-specific import price inflation rates to the values of those inflation rates after subtracting the estimated contributions from movements in the dollar and foreign producer price inflation. Table 11 shows average annual import price inflation ($\bar{\pi}$) as well as the implied average annual import price inflation not including dollar and foreign PPI effects, which we call $\bar{\pi}^{ExDollarPPI}$. As can be seen from the last line of the chart, the variance of the

[22]See again Gruber et al. (2016), "Core Import Prices" equation, coefficient on p^*.

import price inflation rates across groups after excluding the estimated contributions from the dollar and foreign PPI change is 0.06, which, compared to the overall variance of 0.30, means that the dollar and foreign PPI measures accounts for 80% of the overall variance of import price inflation across groups. Thus the dollar and foreign inflation together can reasonably well explain the differences in import price inflation rates. That said, there is a large common component of the level of import price inflation beyond these factors, which is captured by the year fixed effects in Equation 18.

Table 11: Average Annual Import Price Inflation

Demographic	Characteristic	$\bar{\pi}$	$\bar{\pi}^{ExDollarPPI}$
Age	Under Age 30	2.16	1.34
	Age 30-60	2.10	1.62
	Over Age 60	1.55	1.34
Education	H.S. Dropout	0.63	1.12
	H.S. Grad.	1.59	1.49
	College Grad.	2.25	1.59
	Post-Grad	2.10	1.57
Race	White	1.85	1.46
	Black	3.14	2.14
	Asian & P.I.	1.92	1.33
Sex	Male	2.05	1.73
	Female	2.18	1.47
Urban/Rural	Urban	2.08	1.64
	Rural	1.46	1.61
	Variance	0.30	0.06

Notes: This table lists average annual import price inflation for each of the 14 demographic characteristics, first from our import price indexes and then from Equation 18 ("Ex Dollar PPI"), excluding the estimated contributions from the dollar and foreign producer price inflation.

5.6 Out-of-Sample Predictions for 2021-2022 Period

Over our sample period, as shown by Figure 2, movements in the dollar and foreign producer price inflation were fairly moderate (compared with longer-run historical standards). However, in the last few years these measures had much sharper movements in a very short period of time. In particular, comparing the value of our dollar and PPI measures in 2022 Q4 with 2020 Q4, we find that the dollar appreciated 8.3% cumulatively (or 4.7% at an annual rate) while foreign producer prices increased by 13.1% cumulatively (or 7.3% at an annual rate). We can use our estimation results from Equation 18 to understand the expected differential impact of these shocks across demographic groups by feeding in the changes in these factors and, together with our estimated coefficients, generate predicted values of the group-specific import price inflation.

One complication of such an exercise is that, in order to sweep out confounding factors, Equation 18 included year fixed effects. There is therefore a common component that should be included to interpret the predicted values of the dependent variable in level terms that is unavailable to us in this out-of-sample prediction– we are essentially recovering "demeaned" predictions. Although the estimates can still be compared to each other meaningfully, the implied level of each is not identified. As a back-of-the-envelope approximation to bring our estimates back to level space, we note that according to the publicly available BLS import price index for all commodities (an imperfect proxy for our measure), import prices rose by about 6.8 percent per year during 2021-2022[23]. Thus we take the average of our predicted values and add back on a common factor to each such that the mean across demographic groups is also 6.8 percent per year.[24]

The results of this calculation are shown in Table 12. As can be seen from the first column of "demeaned" annual import price inflation numbers implied by our specification $\bar{\pi}^{Demeaned}$, the average across groups for 2021–2022 is about 1.7 percent. Since these estimates only are comparable to each other, rather than meaningful in terms of the actual level of import price inflation, the second column adds about 5.1 percentage point of average import price inflation to each of these, so that the average of our level indexes $\bar{\pi}^{Level}$ approximates the 6.8 percent per year import price inflation taken from the public BLS measure of import prices.

Differences across groups in the level of predicted import price inflation are massive. Estimates range from a low single-digit increase in import prices for high school dropouts to a more than 11 percent increase in import prices for Black consumers, a difference of more than 9.5 percentage points of import price inflation per year. To a first-order approximation, this difference in import price inflation implies that Black consumers had about 1 percentage point

[23]The BLS all-commodity price index rose about 30 percent cumulatively from 1996-2018. We can also compute a consumer product version of BLS import prices by equally weighting the categories "Foods, Feeds, and Beverages", "Fuels and Lubricants", and "New and used cars", and then equally weighting that block with the category "Consumer goods ex Autos" (which is roughly in-line with 2019 trade shares). This consumer measure also rose around 30 percent from 1996-2018, although it rose at a 7.4 percent annual rate 2021-2022.

[24]The simple average we use is obviously also imperfect, since if we had included more or fewer demographic characteristics, the average would change. Generating weighted averages over demographic characteristics is not practical because the characteristics in different demographics are not mutually exclusive. These level estimates are meant to be suggestive only and should be interpreted with caution.

Table 12: Predicted Average Annual Import Price Inflation, 2021–2022

Demographic	Characteristic	$\bar{\pi}^{Demeaned}$	$\bar{\pi}^{Level}$
Age	Under Age 30	3.94	9.06
	Age 30-60	2.09	7.21
	Over Age 60	0.44	5.56
Education	H.S. Dropout	-3.30	1.82
	H.S. Grad.	-0.17	4.95
	College Grad.	3.12	8.24
	Post-Grad	2.34	7.47
Race	White	1.36	6.48
	Black	6.33	11.45
	Asian & P.I.	2.29	7.41
Sex	Male	1.16	6.28
	Female	3.42	8.54
Urban/Rural	Urban	1.72	6.84
	Rural	-1.23	3.89
	Average	1.68	6.80

Notes: This table lists implied average annual import price inflation for each of the 14 demographic characteristics, first implementing the results of Equation 18 ("Ex Dollar PPI") using 2021–2022 movements in the dollar and foriegn PPI, and then by adding a common component to align average import price inflation across groups with the BLS measure of import price inflation during this time.

higher total CPI inflation annually during 2021-2022 than high school dropouts. Why are the differences in import price inflation so large? Recall that dollar appreciation contributes to lower import price inflation while increases in foreign producer prices contributes to higher import price inflation. Since Black consumers have effectively zero dollar pass-through and very high pass-through of foreign producer prices, the particular observed shock from 2021-2022 leads to very high estimates of import price inflation for Black consumers. High school dropouts are at the other end of the spectrum, with high dollar pass-through and low foreign price pass-through. Black consumers also have about 5 percentage points more predicted import price inflation than White consumers. To a first-order approximation, the difference in import price inflation between White and Black consumers implies that Black consumers had about 0.5 percentage point higher total CPI inflation annually during 2021-2022 than White consumers, all else equal. The implied differences in total CPI inflation between consumers under age 30 and over age 60, and differences between college graduates and high school dropouts, are of a similar magnitude. These are large differences in CPI inflation rates given that national CPI inflation was about 6.76 percent annually over the 2021-2022 period.

6 Conclusion

This paper studies how international shocks affect the cost of living of different demographic groups in the United States. Combining information on expenditure shares on imports for a host of demographic characteristics with detailed price data for U.S. imports, we build novel import price indexes for the 1996-2018 period that vary by age, race, sex, education, and urban status. We find that some groups, such as high school dropouts, rural consumers, and consumers over age 60 experienced significantly less import price inflation over the 1996-2018 period than other groups, such as Black consumers and college graduates.

In order to explain the variation in import price inflation across demographic groups, we seek to explain variation in our import price indexes using the trade-weighted exchange value of the dollar and a trade-weighted index of foreign producer prices. We estimate a range of group-specific coefficients on these two factors. Differences in the rate of dollar appreciation passing through to import prices for Black consumers relative to White consumers implies that exchange rate movements would be predicted to lead to an import price decline of 9.4% (all else equal) for White consumers and no decline for Black consumers. Along the same lines, the pass-through of foreign inflation is much larger for consumers under age 30 and Black consumers compared to rural consumers and high school dropouts. In all, we find that 80 percent of the across-group variance in annual import price inflation rates can be explained by these group differences in sensitivity to the dollar and foreign inflation.

Finally, we use the estimated regression coefficients to evaluate the predicted out-of-sample effects on the different demographic groups of the changes in the dollar and foreign producer price inflation that occurred over the 2021-2022 period. According to our estimates, the particular shock observed during the Covid-19 pandemic led to very disparate effects on import prices across demographic groups. The variation in import price inflation rates across demographic groups are large enough to imply sizable differences even in total CPI inflation rates across groups stemming from differential sensitivity to international shocks.

Our findings provide new evidence for the debate over the distributional consequences of exposure to international trade. Our exchange-rate passthrough results in particular are novel results on a new channel for the distributional effects of monetary policy. Future work should consider the distributional effects across other demographic groups beyond those considered here.

References

Atkin, David, Benjamin Faber, and Marco Gonzalez-Navarro, "Retail Globalization and Household Welfare: Evidence from Mexico," *Journal of Political Economy*, 2018, *126* (1), 1–73.

Auclert, Adrien, "Monetary Policy and the Redistribution Channel," *American Economic Review*, 2019, *109* (6), 2333–2367.

_ , Matthew Rognlie, Martin Souchier, and Ludwig Straub, "Exchange Rates and Monetary Policy with Heterogenous Agents: Sizing Up the Real Income Channel," Working Paper 2021.

Auer, Raphael, Ariel Burstein, Sarah Lein, and Jonathan Vogel, "Unequal expenditure switching: Evidence from Switzerland," Working Paper 2022.

Avtar, Ruchi, Rajashri Chakrabarti, Maxim L Pinkovskiy et al., "Was the 2021-22 Rise in Inflation Equitable?," Technical Report, Federal Reserve Bank of New York 2022.

Becker, Randy, Wayne Gray, and Jordan Marvakov, "NBER-CES manufacturing industry database: Technical notes," *NBER Working Paper*, 2013, *5809.*

Borusyak, Kirill and Xavier Jaravel, "The Distributional Effects of Trade: Theory and Evidence from the United States," Working Paper 2017.

Broda, Christian and David Weinstein, "Globalization and the Gains from Variety," *The Quarterly Journal of Economics*, 2006, *121* (2), 541–585.

Burstein, Ariel and Gita Gopinath, "International Prices and Exchange Rates," in "Handbook of International Economics Vol. 4," Elsevier, 2014.

Campa, Jose Manuel and Linda S. Goldberg, "Exchange Rate Pass-through Into Import Prices," *The Review of Economics and Statistics*, 2005, *87* (4), 679–690.

Cravino, Javier and Andrei A. Levchenko, "The Distributional Consequences of Large Devaluations," *American Economic Review*, 2017, *107* (11), 3477–3509.

Faber, Benjamin and Thibault Fally, "Firm Heterogeneity in Consumption Baskets: Evidence from Home and Store Scanner Data," *The Review of Economic Studies*, 2022, *89* (3), 1420–1459.

Fajgelbaum, Pablo and Amit K. Khandelwal, "Measuring the Unequal Gains from Trade," *The Quarterly Journal of Economics*, 2016, *131* (3), 1113–1180.

_ **, Gene M. Grossman, and Elhanan Helpman**, "Income Distribution, Product Quality, and International Trade," *Journal of Political Economy*, 2011, *119* (4), 721–765.

Feenstra, Robert C., "New Product Varieties and the Measurement of International Prices," *The American Economic Review*, 1994, pp. 157–177.

_ **and David E. Weinstein**, "Globalization, Markups, and U.S. Welfare," *Journal of Political Economy*, 2017, *125* (4), 1040–1074.

Furman, Jason, Katheryn Russ, and Jay Shambaugh, "U.S. Tariffs are an Arbitrary and Regressive Tax," *VoxEU.org. http://voxeu.org/article/us-tariffs-are-arbitrary-and-regressive-tax*, 2017.

Gailes, Arthur, Tamara Gurevich, Serge Shikher, and Marinos Tsigas, "Gender and Income Inequality in United States Tariff Burden," *US International Trade Commission Working Paper*, 2018, (2018-08).

Gopinath, Gita, Oleg Itskhoki, and Roberto Rigobon, "Currency Choice and Exchange Rate Pass-Through," *American Economic Review*, 2010, *100* (1), 304–336.

Gruber, Joseph W, Andrew H McCallum, and Robert J Vigfusson, "The dollar in the US international transactions (USIT) model," Technical Report, Board of Governors of the Federal Reserve System (US) 2016. `https://www.federalreserve.gov/econresdata/notes/ifdp-notes/2016/the-dollar-in-the-us-international-transactions-model-20160208.html`.

Hobijn, Bart, Kristin Mayer, Carter Stennis, and Giorgio Topa, "Household inflation experiences in the US: a comprehensive approach," Working Paper, Federal Reserve Bank of San Francisco 2009.

Hottman, Colin J. and Ryan Monarch, "A matter of taste: Estimating import price inflation across US income groups," *Journal of International Economics*, 2020, *127.*

_ **, Stephen J. Redding, and David E. Weinstein**, "Quantifying the Sources of Firm Heterogeneity," *The Quarterly Journal of Economics*, 2016, *131* (3), 1291–1364.

Kamal, Fariha and C.J. Krizan, "Decomposing Aggregate Trade Flows: New Evidence from U.S. Traders," Working Paper 12-17, U.S. Census Center for Economic Studies 2012.

— **and Ryan Monarch**, "Identifying Foreign Suppliers in U.S. Import Data," *Review of International Economics*, 2018, *26* (1), 117–139.

Lee, Munseob, Claudia Macaluso, and Felipe Schwartzman, "Minority unemployment, inflation, and monetary policy," Working Paper 2021.

— **et al.**, "Do Black Households Face Higher and More Volatile Inflation?," *Richmond Fed Economic Brief*, 2022, *22* (25).

McGranahan, Leslie and Anna L Paulson, "The incidence of inflation: inflation experiences by demographic group: 1981-2004," Technical Report, FRB of Chicago Working Paper No. WP-05-20 2005. `http://www.chicagofed.org/digital_assets/publications/working_papers/2005/wp2005_20.pdf`.

McKay, Alisdair and Christian K Wolf, "Monetary Policy and Inequality," *Journal of Economic Perspectives*, 2023, *37* (1), 121–144.

Monarch, Ryan, "It's Not You, It's Me: Prices, Quality, and Breakups in U.S.-China Trade Relationships," *Review of Economics and Statistics*, 2022, *104* (5), 909–928.

Neary, J. Peter, "Rationalizing the Penn World Table: True Multilateral Indices for International Comparisons of Real Income," *The American Economic Review*, 2004, *94* (5), 1411–1428.

Porto, Guido, "Using Survey Data to Assess the Distributional Effects of Trade Policy," *Journal of International Economics*, 2006, *70*, 140–160.

Redding, Stephen J. and David E. Weinstein, "Aggregating From Micro to Macro Patterns of Trade," NBER Working Paper 24051, 2017.

— **and** — , "Measuring Aggregate Price Indices with Taste Shocks: Theory and Evidence for CES Preferences," *The Quarterly Journal of Economics*, 2020, *135* (1), 503–560.

Schott, Peter K, "The relative sophistication of Chinese exports," *Economic Policy*, 2008, *23* (53), 6–49.

Simonovska, Ina, "Income Differences and Prices of Tradables: Insights from an Online Retailer," *The Review of Economic Studies*, 2015, *82* (4), 1612–1656.

Taylor, Lori L and Jawad Dar, "Fairer trade, removing gender bias in US import taxes," Working Paper 2015.

Appendix

A Data Appendix

A.1 Expenditure Share Construction

We start by replicating publicly available UCC-level expenditures by using the CE microdata for particular characteristic groups. The microdata has households identified by “NEWID", and the data is at the NEWID-UCC expenditure level, both for diary UCCs and for interview UCCs. We have a) a list of UCCs, b) expenditure on some UCCs by NEWID, and c) the characteristics of particular NEWIDs. To build UCC-NEWID expenditures in a way that will lead to proper weighting, for both diary and interview, we:

1. Save a dataset listing the UCCs and expand by the number of NEWIDs, so that the total size of the dataset is # NEWID x # UCCs. (Dataset A)

2. Save a dataset that contains NEWID expenditure on particular UCCs (not the whole set of UCCs). (Dataset B)

3. Make a NEWID-level dataset, keeping the characteristics for each one as well as the weights for each NEWID.

4. Expand the dataset so that each NEWID has a slot for every UCC code.

5. Merge on Dataset A (1:1 _n), so each NEWID has every UCC code.

6. Merge on Dataset B (1:1), so that, where available, each NEWID has expenditure on a particular UCC. Replace missing expenditure observations with zeroes.

Constructing the data in this way means that when applying the calibration weights to each household generates expenditure on each UCC code for any given demographic characteristic.

Our estimated expenditures line up well with published data, as shown in Figure A.1, which plots individual category spending in the published CE tables with our estimates constructed from the PUMD for different age groups.

Next, we decide which characteristics we want to have in the data. We pick characteristics such that the number of household observations underlying each characteristic or set of characteristics is not too small (we try to obtain more than 2,000 NEWID observations in 2018). Table A.1 shows some of the characteristics available in the CE data. We take these variables and convert them into the groupings for the years 1996 through 2018, as shown in Table A.2. Table A.3 shows the household observation counts for each of our chosen groupings in 2018.

Table A.1: List of Characteristics, CE data

Characteristic	Variable	Value	Availability
Race	RACE / MEMRACE	1=White 2=Black 3=Amer. Ind. 4=Asian	1990 -
Age	AGE	Numeric Age	1990-
Urban	BLS_URBN	1=Urban, 2=Rural	1984-
Education	EDUC_REF	11 = High School, No degree 12= High School Graduate 13 = Some College, no degree 14 = Associate's degree 15 = Bachelor's degree 16 = Master's, Professional, or Doctorate degree	1996-
Sex	SEX	1 = Male 2 = Female	1990-

Table A.2: List of Characteristics for Import Data

Characteristic	Value	Number of Groups
Race	1=White 2=Black 3=Asian and P.I.	3
Age Range	1= <30 , 2=30-60 , 3=61+	3
Urban	1=Urban 2=Rural	2
Education	1= H.S. Dropout 2= H.S. Graduate 3= College Graduate 4= Post-Graduate	4
Sex	1 = Male 2=Female	2

Figure A.1: CE Expenditure for UCC Products by Age

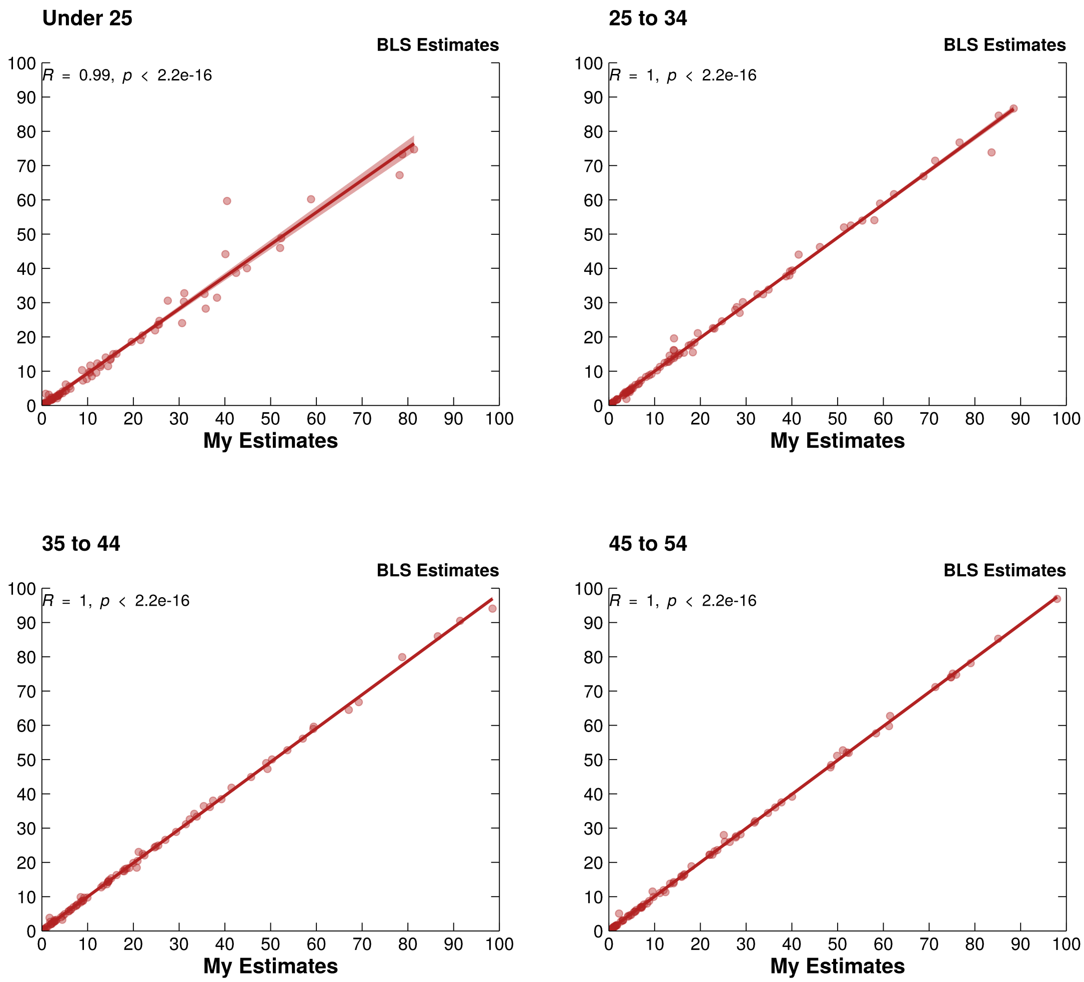


Table A.3: Selected Demographic Characteristics in the Consumer Expenditure Survey

Demographic	Characteristic	Number of Households (2018)
Age	Under Age 30	4,565
	Age 30-60	21,228
	Over Age 60	13,918
Education	High School Dropout	3,894
	High School Graduate	17,246
	College Graduate	13,183
	Post-Graduate	5,429
Race	White	32,506
	Black	4,173
	Asian & P.I.	2,205
Sex	Male	19,146
	Female	20,565
Urban/Rural	Urban	37,189
	Rural	2,672

Notes: This table summarizes the number of households for a particular generated characteristic within the selected demographic group.

A.2 Dollar Index Construction

The Broad Dollar Index is constructed by using the currencies of the most important U.S. trading partners by volume of bilateral trade. The index is a geometrically weighted average of changes in bilateral exchange rates. The index at time t I_t is:

$$I_t = I_{t-1} * \Pi_{j=1}^{N}(t) \frac{e_{j,t}}{e_{j,t-1}}^{w}{}_{j,t} \tag{19}$$

where Π is the product operator, I_{t-1} is the value of the index at time $t-1$; $e_{j,t}$ and $e_{j,t-1}$ are the prices of the U.S. dollar in terms of foreign currency j at times t and $t-1$; $w_{j,t}$ is the weight of currency j in the index at time t; $N(t)$ is the number of foreign currencies in the index at time t; and the weights sum to one ($\sum_j w_{j,t} = 1$). Currency weights for the broad dollar index are determined by each country's proportion of imports and exports as compared with total imports and exports.

For the construction of our HS6-based dollar index, the same set of countries was used as the Broad Dollar Index, which are part of the Federal Reserve's H.10 Statistical Release.[25] For the years 1996-1998 (prior to the introduction of the Euro), we proxied Eurozone trade as a combination of German, French, Italian, and Dutch imports; these four countries were the largest Eurozone trading partners at the introduction of the Euro and accounted for 93 percent of all goods imports with the European Union in 1999[26]. Exchange Rate data was taken from the IMF International Financial Statistics ("IMF-IFS") database in both quarterly and annual form[27].

Data regarding US Goods Imports and Exports were from the US Customs Service and Schott (2008): they record the customs value of all US imports and exports by exporting country and year from 1996-2021, classified by the 10-digit Harmonized System (HS) codes. For each year, these data were trimmed to include only countries, regions, and territories used in the construction of the index, as well as only the relevant product codes. Currency weights were assigned using each country's proportion of imports to the U.S. according to the list of goods under consideration.

[25] The list of countries, regions and territories used in the Broad Dollar Index are: Argentina, Australia, Brazil, Canada, Chile, China (Hong Kong), China (Mainland), China (Taiwan), Colombia, the Eurozone, India, Indonesia, Israel, Italy, Japan, South Korea, Malaysia, Mexico, The Netherlands, The Philippines, The Russian Federation, Saudi Arabia, Sweden Switzerland, Thailand, The United Kingdom, and Vietnam.

[26] https://www.census.gov/foreign-trade/balance/c0003.html1999

[27] The specific indicator used was "Exchange Rates, National Currency Per U.S. Dollar, Period Average, Rate" for the years 1996 to 2022.