The Distributional Effects of Trade: Theory and Evidence from the United States*

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Abstract

How much do consumption patterns matter for the impact of international trade on inequality? In neoclassical trade models, the effects of trade shocks on consumers' purchasing power are governed by the shares of imports in consumer expenditures, under no parametric assumptions on preferences and technology. This paper provides in-depth measurement of import shares across the income distribution in the United States, using new datasets linking expenditure and customs microdata. Contrary to common wisdom, we find that import shares are flat throughout the income distribution: the purchasing-power gains from lower trade costs are distributionally neutral. Accounting for changes in wages in addition to prices in a unified nonparametric framework, we find substantial distributional effects that arise within, but not across, income and education groups. There is little impact of a fall in trade costs on inequality, even though trade shocks generate winners and losers at all income levels, via wage changes.

Keywords: Trade liberalization, Distributional effects, Inequality, Non-homothetic preferences

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1 Introduction

How much do consumption patterns matter for the impact of international trade on inequality? Some households benefit from the global economy by buying products manufactured abroad or using imported inputs. If the poor buy disproportionately more imported products, then trade liberalizations may reduce purchasing-power inequality. Whether or not this is the case empirically remains debated to this day: because of data constraints, we still lack direct and comprehensive empirical evidence on the import shares in the consumption baskets of different income groups, even in widely-studied countries, such as the United States. Furthermore, it is not clear how consumption heterogeneity compares and interacts with the labor market effects of trade in shaping the distributional effects of trade shocks.[1]

This paper provides new evidence on the heterogeneous effects of trade shocks through both consumer prices *(expenditure channel)* and wages *(earnings channel)* across and within income and education groups, and thus on the net distributional effects. Our analysis is based on linked datasets that cover the consumption and production sides of the entire U.S. economy and leverage detailed expenditure microdata on consumer packaged goods and motor vehicles merged with restricted access customs data. Contrary to common wisdom, we show that the expenditure channel of trade is close to distributionally neutral in the United States. Taking into account the earnings channel and general equilibrium effects, we find distributional effects of trade shocks that are primarily concentrated *within* groups of workers with similar initial earnings, while the effect on overall inequality is small. In this sense, the distributional effects of trade shocks are mostly "horizontal" (within income deciles) rather than "vertical" (across deciles).

A key contribution of this paper is the in-depth measurement of import shares across the income distribution. We motivate this analysis by showing that in neoclassical trade models the welfare effects of small, uniform counterfactual trade shocks are fully governed by observed import shares.[2] While this theoretical result, in the spirit

[1]Canonical and more recent trade theories predict that trade should negatively impact the earnings of low-skilled and low-paid workers in the U.S. (e.g., Stolper and Samuelson (1941), Burstein and Vogel (2017), Caron et al. (2020), and Cravino and Sotelo (2019)), but these studies do not allow for heterogeneity in consumption baskets within countries.

[2]Our definition of welfare effects is the equivalent variation measured as a fraction of initial expenditures. In dollar terms, the effects have to be rescaled by total expenditures, which are higher for richer households.

of Deaton (1989), applies in partial equilibrium and under some conditions which we specify, it requires no parametric assumptions on preferences and technologies.

To measure import shares across the income distribution accurately and comprehensively, we build three complementary datasets, focusing on the year 2007. First, we match the Consumer Expenditure Survey (CEX) to the U.S. Input-Output table to jointly measure income-specific expenditure shares and import shares for 170 industries that cover all goods and services. We then complement it with detailed microdata for two spending categories which cover around 40% of total expenditures on tradable goods: consumer packaged goods and motor vehicles. These datasets are essential to address potential aggregation biases in import shares, e.g. if low-income consumers buy more imported varieties within categories. For consumer packaged goods, we build a firm-level link between the Nielsen Homescan Consumer Panel, as a source of detailed consumption baskets, and the Economic Census and Customs microdata, as a source of import shares. For motor vehicles, we similarly match the CEX with Ward's Automotive Yearbooks and the Census of Manufactures. In each of the three analyses we account for both imported final goods and imported inputs in domestic goods. To the best of our knowledge, this paper is the first to document the expenditure channel of trade with a direct measurement approach covering all industries of the economy, including the role of imported intermediate inputs, and allowing for heterogeneity in import shares arising across firms within the same industries.

Comparing income and education groups, we find that there is no difference in import shares arising *across* industries, i.e. from industry-level heterogeneity in consumption baskets; *within* industries, richer and more educated individuals have a slightly higher spending share on imports. In the aggregate, imports account for 12.6% of expenditures, and this share varies only slightly across income groups in the industry-level data, hovering non-monotonically between 11.7% and 12.9% across the income distribution. Within consumer packaged goods, we find that higher-income households buy more imports, except from China, but these differences are relatively small, varying from about 10.3% at the bottom to about 11.6% at the top. Finally, import shares for vehicles are flat around 44% across most of the income distribution, except for a marked increase to 50% for those earning above $150,000 a year.

These results run counter to both the common wisdom and findings from prior work on the expenditure channel (Fajgelbaum and Khandelwal 2016) which suggest that low-income U.S. households consume more imports and benefit more from trade through lower prices. To reconcile the findings, we first explain theoretically that the Almost Ideal Demand System (AIDS) employed by Fajgelbaum and Khandelwal (2016) mechanically generates a strong pro-poor expenditure channel. We then estimate a nested version of the non-homothetic CES demand system (e.g. Comin et al. 2021), which does not possess the mechanical features of AIDS, and find that the expenditure channel of trade becomes small, consistent with our direct measurement. This analysis shows that the choice of the demand system can have a large quantitative impact on the estimated expenditure channel, highlighting the value of our data-driven approach.

In the remainder of the paper, we study the distributional effects of trade shocks in general equilibrium, offering a unified analysis of the expenditure and earnings channels. This analysis requires additional assumptions on the structure of the economy, such that the factor market equilibrium response to trade shocks can be characterized. Our framework preserves the key advantage of our data-driven approach to the expenditure channel: the welfare effects of counterfactual trade shocks are represented in terms of intuitive sufficient statistics that capture heterogeneous exposure to international trade.

We provide a novel characterization for the changes in factor demand and factor prices induced by small shocks to trade costs. This characterization holds in a class of quantitative trade models with standard assumptions on the labor and product markets allowing for a broad set of preferences and production functions. We show that changes in factor demand can be decomposed into several terms corresponding to different mechanisms: exporting, import competition, imported intermediate inputs, income and substitution effects. Each of these terms is governed by an intuitive statistic measuring exposure to international trade — similar to our analysis of the expenditure channel, but now arising from the factor market. For instance, a factor whose employment is concentrated in industries that have high export ratios, directly or indirectly, will see factor demand grow after a trade liberalization, *ceteris paribus*. How factor prices respond to factor demand in turn depends on the elasticities of aggregate factor demand. Our characterization highlights a new mechanism: given exposure, the welfare gains through the earnings channel are stronger for the factor specialized in non-traded industries, as factor demand is less elastic in these industries.

Taking our characterization to the data, we evaluate a counterfactual where trade costs fall by 10% with all trading partners. We also assess the impacts of other shocks, including a trade liberalization with China specifically, historical reductions in trade costs, and the introduction of the "Trump tariffs" in 2018. Our theoretical results allow for any factor types, but empirically we consider different groups of workers in the main analysis and study capital in a robustness check. To assess both vertical and horizontal distributional effects, i.e. the unequal effects of trade shocks both across and within income groups, we first consider a calibration in which there is no mobility of workers across industries.[3]

The key lesson that emerges from this empirical analysis is that exposure differences and the corresponding distributional effects are primarily concentrated within income groups, rather than across. Over 99% of the variance of welfare changes arise within income deciles. There is little impact of a fall in trade costs on overall inequality, despite the substantial distributional effects that generate sizable changes in relative income as well as winners and losers at all income levels. The spread between the 10th and 90th percentiles of welfare effects is over 2 percentage points within each decile, while variation across deciles is much smaller: all groups benefit on average and the gains are slightly higher for poorer households, ranging from 2.0% in the bottom decile to 1.8% for the top decile.[4]

Higher gains for poor households may look surprising, in particular in light of the canonical Heckscher-Ohlin model. Consistent with the Stolper-Samuelson theorem, in our calibration relative labor demand for low-income workers falls after the trade shock. Yet, an offsetting force dominates: low-income workers are employed relatively more in service industries, which have lower labor demand elasticities; as a result, a given labor demand shock induces, on average, a stronger wage response for them.

To confirm that there are no strong distributional effects *across* groups of ex-ante similar workers, we conduct a similar analysis across education groups. In this second calibration, we consider two groups of workers — those with and without a college

[3]In that case, each worker's labor market exposure is simply her industry's exposure. While the assumption of no mobility may be most appropriate in the short-run, this analysis can be generalized to the case where labor mobility follows a Roy model with a finite but non-zero elasticity of industry labor supply, as in Galle et al. (2020). We have no reason to expect that the key lesson presented below would change in that medium-run model.

[4]These differences are due to the earnings channel, with the expenditure channel still mostly flat when accounting for the general equilibrium effects. Thus, the interaction between the expenditure and earnings channels, allowed for in the model, turns out to be quantitatively small.

degree — and assume perfect mobility across industries. We again find that the effects are very similar across groups. The welfare gain from the 10% fall in trade costs is 1.7% for college-educated workers, compared with 1.6% for those without a college degree. All our findings therefore go against a popular narrative that "trade wars are class wars" (Klein and Pettis 2020).

This paper contributes to the growing literature on the distributional effects of trade through the expenditure channel. Several papers rely on the structure of the demand system to (implicitly) infer differences in import spending across consumer groups from aggregate trade flows. Fajgelbaum and Khandelwal (2016) and He (2020) found strong pro-poor effects of the expenditure channel for all countries, while the estimates of Nigai (2016) are pro-rich. In contrast, the estimates reported in this paper are based on direct observation of consumption baskets for both domestic and imported products and therefore require minimal structural assumptions to characterize the magnitude of the expenditure channel.

Several papers directly measure spending on imports across consumer groups: Porto (2006) for Argentina, Faber (2014) for Mexico, Levell et al. (2017) and Breinlich et al. (2017) for the U.K., Auer et al. (2021) for Switzerland, and Hottman and Monarch (2020) for the U.S. Data limitations make these papers focus only on particular types of differences in expenditure shares.[5] In contrast, our paper is the first to consider the entire economy, taking into account imports of both final and intermediate goods, and at the same time using very detailed data on consumer packaged goods and motor vehicles to address potential aggregation biases.[6]

[5]Porto (2006) captures differences in spending across 7 large categories of final goods and services, Faber (2014) looks at imported intermediate inputs only, Levell et al. (2017) limit their analysis to 9 categories of food, and Breinlich et al. (2017) consider 12 broad groups of goods and services consumed by households. In contemporaneous work, Hottman and Monarch (2020) also use CEX to show that import spending is similar across income groups, but they do not account for intermediate inputs and only have industry-level expenditure data. In work subsequent to ours, Auer et al. (2021) analyze import shares in Nielsen scanner data, without accounting for sectors other than fast-moving consumer goods. In related papers, Furman et al. (2017) and Gailes et al. (2018) merge the CEX consumption data by group with import shares but, focusing on the incidence of tariffs, do not report differential import spending.

[6]While we focus on counterfactual shocks, a related literature evaluates the heterogeneous effects of historical trade shocks on U.S. prices: Amiti et al. (2020) and Jaravel and Sager (2020) quantify the reduction of U.S. prices due to trade with China; Bai and Stumpner (2019) further show that the effects of trade with China on prices and product variety were similar in industries selling to richer and poorer households; and Hottman and Monarch (2020) show that lower-income households experienced larger growth of import prices between 1998 and 2014.

Our paper also contributes to the literature characterizing the effects of trade on wage inequality using sufficient statistics. The early literature, guided by the Heckscher-Ohlin model, looked at the net factor content of trade (e.g. Katz and Murphy (1992), Deardorff and Staiger (1988), Krugman (2000)). More recently, Burstein and Vogel (2017) and Cravino and Sotelo (2019) show that this statistic is not appropriate in richer models. Our characterization provides a set of sufficient statistics in a modern, multi-sector gravity model. It allows us to quantify the role of multiple mechanisms in a unified way and assess their relative importance: e.g., the role of skill endowment emphasized by the Stolper-Samuelson theorem, the contributions of non-homothetic preferences (Caron et al. 2020), and the complementarity between goods and services (Cravino and Sotelo 2019). In independent subsequent work, Adão et al. (2020) develop a different decomposition for factor price changes due to trade, into import and export channels, and apply it to detailed firm-level data in Ecuador. Our results allow for non-homothetic demand, incorporate and isolate additional channels, and analyze the United States.[7]

On the empirical side, our results are related to Galle et al. (2020) who show, by using exact hat algebra in a multi-sector gravity model, that the China shock generates strong distributional effects. Our contribution is to quantify the extent to which the distributional effects of the shocks we study are "horizontal" rather than "vertical," which to the best of our knowledge has not been studied in prior work.[8] Because of data limitations, we do not consider the regional dimension of the effects of trade, which has been emphasized by Autor et al. (2013) and could be studied using our exposure-based approach given appropriate data.[9]

[7]While our theoretical results are most suited to study small shocks to trade costs, Adão et al. (2020) focus on the autarky counterfactual. Compared with Proposition 3 in Adão et al. (2020), we allow for flexible income and substitution effects, modeled with nested non-homothetic CES preferences across industries. We also capture the effects of import competition in intermediate demand (rather than in final demand only), making our model consistent with the standard industry-level gravity equation. We isolate the negative effects of import competition from the positive productivity effects of imported intermediate inputs. Compared to our paper, Adão et al. (2020) leverage rich data on firm-to-firm transactions and on capital ownership.

[8]This point is distinct from the line of work on the role of trade for "residual" inequality, i.e. wage dispersion within occupations and sectors (e.g., Helpman et al. 2017). Residual inequality is a component of the overall wage inequality, whereas horizontal distributional effects generate winners and losers without affecting inequality.

[9]This line of work has largely been silent about the effect of trade on wage inequality: Autor et al. (2013) do not find significantly different cross-sectional effects on skilled and unskilled wages (see Tables 6 and 7) and do not document the distribution of trade shocks across commuting zones.

Finally, we contribute to an emerging literature that analyzes the expenditure and earnings channels jointly, in a unified framework. There are only two papers in this space: Porto (2006) uses time-series regressions to estimate the impact of trade-induced price changes on wages and domestic prices, while He (2020) generalizes the structural model of Fajgelbaum and Khandelwal (2016). We take a different approach by focusing on a set of exposure statistics measured in detailed data.

The remainder of the paper is organized as follows. Section 2 shows how to connect import shares to the expenditure channel and presents the data sources. Section 3 estimates import shares across the income distribution and other household groups. Section 4 reconciles the results of our direct measurement approach with those based on parametric assumptions. Section 5 presents the theoretical framework and the estimates of the distributional effects from counterfactual trade shocks in general equilibrium. Section 6 concludes.

2 Conceptual Framework and Data

In this section, we first characterize the conditions under which the welfare effects of trade shocks via the expenditure channel are fully governed by import shares in consumer expenditure. We then describe the data sources we use to measure heterogeneity in import shares across household groups.

2.1 Import Shares as Sufficient Statistics

We consider a set of infinitesimal price changes due to a decline in iceberg trade costs in a static setting. We adopt the standard approach defining the change in welfare for consumer group i as the equivalent variation EV_i divided by initial expenditures X_i (Deaton 1989; Fajgelbaum and Khandelwal 2016), which we denote $d\log\mathcal{W}_i$. For example, $d\log\mathcal{W}_i$ is equal to 0.01 if the trade liberalization is equivalent, in utility terms, to increasing total spending by 1% at the original prices. Consumers maximize utility over a set of differentiated products indexed by ω, with expenditure shares

They instead find negative effects of trade with China on manufacturing employment in the U.S. at the level of commuting zones (and industries in Acemoglu et al. (2016)), which is consistent with our model.

denoted by s^i_ω.[10]

Trade costs affect prices faced by domestic consumers through three channels: prices of final goods imported from abroad, costs of production and prices of domestic goods that use imported intermediate inputs, and general equilibrium adjustments to domestic production costs, including wage changes for different domestic factors and terms of trade effects.

We formalize the conditions under which differences in the import shares of consumption baskets across consumer groups are sufficient statistics for the expenditure channel. Specifically, we consider a reduction in iceberg trade costs between Home and a foreign country (or a set of countries) c that is uniform across products: $d\log\tau_\omega \equiv d\log\tau < 0$ for each ω imported from c ($\omega \in \Omega_c$), with $d\log\tau_\omega = 0$ otherwise. We aim to show that its welfare effect is given by:

$$\frac{d\log\mathcal{W}_i}{-d\log\tau} = ImpSh^i_c, \tag{1}$$

where the import share in expenditures is defined as

$$ImpSh^i_c = \underbrace{\sum_{\omega\in\Omega_c} s^i_\omega \cdot 1}_{\text{Direct}} + \underbrace{\sum_{\omega\in\Omega_H} s^i_\omega \widetilde{IP}^{\text{Int}}_{\omega c}}_{\text{Indirect}}.$$

Here indirect import share $\widetilde{IP}^{\text{Int}}_{\omega c}$ for a domestic product $\omega \in \Omega_H$ is the share of intermediate inputs from c in ω's total cost, accounting for all domestic input-output (IO) linkages.[11] This result follows from three assumptions.

Assumption 1 (Neoclassical economy)**.** *All product and factor markets are perfectly competitive, and all production technologies have constant returns to scale and differentiable cost functions.*

Under Assumption 1, prices are continuous in trade costs. Hence, by the envelope theorem (Roy's identity), consumer price changes $d\log p_\omega$ affect each consumer group in proportion to the spending shares s^i_ω, and

$$d\log\mathcal{W}_i = d\log X_i - \sum_\omega s^i_\omega d\log p_\omega, \tag{2}$$

[10] Throughout the paper, we indicate buyers in the superscripts and sellers in the subscripts. Agents are buyers in the product markets and, in Section 5.1, sellers in the labor market.

[11] We use tildes to denote objects that account for upstream suppliers. Indirect import shares are defined recursively by $\widetilde{IP}^{\text{Int}}_{\omega c} = \sum_{\ell\in\Omega_c}\beta^\omega_\ell \cdot 1 + \sum_{\ell\in\Omega_H}\beta^\omega_\ell \widetilde{IP}^{\text{Int}}_{\ell c}$, where β^ω_ℓ are the shares of ℓ inputs in the unit costs of $\omega \in \Omega_H$.

where $d \log X_i$ is the change in total expenditures. This equation holds regardless of the demand system (see Appendix A for the proof).[12]

Assumption 2 (Partial equilibrium)**.** *Factor prices do not change at Home or abroad.*

Under Assumption 2, the second term in equation (2), corresponding to the change in the cost of living, is entirely responsible for the welfare gain. We relax this assumption in the general equilibrium version of the model in Section 5.1.

Assumption 3 (No domestic value in imports)**.** *Products imported into Home contain no inputs previously exported from Home.*

Assumption 3 does not preclude global value chains (GVCs) involving foreign countries but allows us to disregard the fact that the domestic economy may be embedded into GVCs. Appendix S.1 relaxes this assumption for our theoretical results, but data constraints make it challenging to implement the formulas at a granular level of observation. As a result, we focus on domestic IO linkages abstracting from GVCs in our empirical analysis.

Assumptions 1–3 combined allow us to solve for the price changes. By Assumption 1 the incidence of the trade shocks falls entirely on consumers due to complete pass-through.[13] For imported products, price changes are equal to the underlying changes in iceberg trade costs of importing, i.e. $d \log p_\omega = d \log \tau$ for $\omega \in \Omega_c$. By Assumptions 1–2 and the envelope theorem (Shephard's lemma), the unit cost of domestic production adjusts in proportion to the use of imported intermediates. By Assumption 3 it is sufficient to consider domestic IO linkages, which yields $d \log p_\omega = \widetilde{IP}^{\text{Int}}_{\omega c} d \log \tau$ for $\omega \in \Omega_H$. This leads to our first proposition, which motivates our empirical investigation of import shares in consumption baskets (see Appendix A for the proof).

Proposition 1. *Suppose Assumptions 1–3 are satisfied. Then equation (1) holds.*

[12] In Appendix S.1 we show the conditions under which (2) applies with endogenous product entry and exit, e.g. as in Eaton and Kortum (2002) or the generalized Melitz-Pareto model of Kucheryavyy et al. 2020.

[13] Complete pass-through is consistent with the estimates from Trump tariffs by Fajgelbaum et al. (2020) and Amiti et al. (2019). Models with complete pass-through and intermediate inputs can also accommodate the empirical finding that final consumer prices adjust less than border prices in response to trade or exchange rate shocks (Goldberg and Campa 2010), as well as exchange rate disconnect (Amiti et al. 2014).

In Appendix S.1, we show how to relax Assumptions 1–3, allowing for global value chains, markups and incomplete pass-through, expanding product variety, and returns to scale. In these extensions, import shares continue to play an important role for the expenditure channel but require model-specific adjustments. In Section 5 we further allow for changing domestic factor prices, quantifying their impact on the expenditure channel (in addition to the earnings channel), and analyze non-uniform changes in trade costs.

Finally, we introduce a decomposition for the heterogeneity in import shares that will structure our empirical work. Such heterogeneity may arise at different levels of product aggregation. For example, a group of consumers may purchase relatively more imports because it spends more on manufactured goods relative to services (between-industry heterogeneity), or because it buys more imported fruit relative to domestically-produced fruit (heterogeneity within detailed industries). Classifying products ω into broader categories r, the difference in import shares between some consumer group i and the representative consumer in the country, denoted by $i = 0$, can be decomposed as

$$ImpSh_c^i - ImpSh_c^0 = \underbrace{\sum_r \left(s_r^i - s_r^0\right) ImpSh_{rc}^0}_{\text{Between}} + \sum_r s_r^i \underbrace{\left(ImpSh_{rc}^i - ImpSh_{rc}^0\right)}_{\text{Within}}, \quad (3)$$

where $ImpSh_{rc}^i = \left(\sum_{\omega \in r \cap \Omega_c} s_\omega^i \cdot 1 + \sum_{\omega \in r \cap \Omega_H} s_\omega^i \widetilde{IP}_{\omega c}^{\text{Int}}\right) / s_r^i$ is the average import share of products in group i's expenditures in r, and $s_r^i = \sum_{\omega \in r} s_\omega^i$ is the spending share of group i on all products in r. Similar decompositions hold when there are additional aggregation levels.

Armed with this decomposition, we will measure the "between" and "within" terms separately using complementary datasets. With industry-level data on the entire U.S. economy and tracing input-output linkages, we will measure the between term. We will then collect data disaggregated by the producing firm or brand and measure the within terms for consumer packaged goods and motor vehicles.[14]

[14] Besides guiding our empirical analysis, another use of the within-between decomposition is to shed light on whether trade policy can be targeted to reduce cost-of-living inequality. Since tariffs are typically imposed at the level of product categories, rather than individual firms and products, such targeting will not be effective if heterogeneity in import shares mostly arises within categories.

2.2 Data Construction

We now describe three linked datasets we develop to measure import shares across the income distribution as accurately and comprehensively as possible. The details of data construction are reported in Appendices S.2.1–S.2.3, while Supplementary Table S1 presents the summary statistics.

The entire economy at the industry level: CEX-IO data. We first measure import shares by consumer group at the industry level, covering the universe of goods and services. We combine the Consumer Expenditure Survey (CEX) with the U.S. Input-Output table. For a representative sample of households, the CEX reports expenditures on all goods and services by 668 detailed spending categories, yielding expenditure shares by income and education group. The IO table, in turn, allows us to measure both direct and indirect import shares for 389 six-digit industries. We use additional tabulations from the U.S. Census Bureau to compute import shares for specific trading partners: China, NAFTA countries (Mexico and Canada), and 34 developed economies (OECD members, excluding NAFTA, plus Taiwan and Singapore). We focus on the year 2007, the most recent year for which the detailed IO table is available; we check robustness to other years with more aggregated data. Matching CEX spending categories to final consumption industries in the IO table, we obtain a dataset with both consumer group-specific expenditure shares and total (direct plus indirect) import shares across 170 final IO industries.

Consumer packaged goods at the firm level: Nielsen-Census data. We then measure import shares by consumer group for consumer packaged goods — goods typically purchased in supermarkets. We use detailed expenditure data from the Nielsen Homescan Consumer Panel (henceforth Nielsen) and match them to the confidential U.S. Census Bureau data on domestic production and imports at the firm level.

The Nielsen data record spending by a representative panel of households at the level of barcode. The data cover three product classes: (i) food, alcohol, and tobacco (henceforth "food"), (ii) health, beauty, and household products (henceforth "health and household"), and (iii) general merchandize (e.g., tableware, stationery, and some electronics). These products are classified into 1,165 product modules (e.g. Frozen Soup), which we match to 71 IO industry codes. Overall, the data cover around

30–35% of expenditures on goods.[15]

To measure the direct and indirect import share of each barcode, we find the product's manufacturer or distributor in the confidential U.S. Census data. We proxy for a product's import share by the ratio of imports (measured in the Customs dataset, LFTTD) to total sales of the corresponding firm. This measure captures imports of both final products and intermediate inputs (except those imported through a domestic intermediary). It is also available for imports from China, NAFTA, and 34 developed economies specifically.

To obtain the linked dataset, we build a novel match between Nielsen barcodes and firms in the Census datasets, which yields 12,700 matched firm-years for years 2007 and 2012, covering 83% of consumer packaged goods sales. The multi-step procedure for matching is described in the Appendix, along with adjustments for multi-product firms, match statistics, quality checks, and examples.

Motor vehicles at the brand level: CEX-Ward's and CEX-Census data. Finally, we measure import shares by consumer group for motor vehicles, which account for 8% of personal expenditures on goods, according to the IO table.

We rely on the vehicle ownership data from the CEX, which asks households to report the brands of cars and light trucks (e.g., SUVs) they own, allowing us to measure the fractions of brands by income and education groups. Chevrolet and Buick are examples of brands, which are more detailed than firms (e.g. Chevrolet and Buick are both produced by GM) but not as detailed as models (e.g. Chevrolet Camaro). We combine the CEX with Ward's Automotive Yearbooks (henceforth Ward's) — a leading publication for statistics on the automotive industry — as a source of import shares for each brand. Ward's provides information on the country of assembly of each model, from which we measure import shares by brand. We pool the data for 2009–2015 to reduce noise in both datasets. Our final sample includes 45 brands and 99,048 vehicles.

We also investigate the role of imported car parts, which are not accounted for in the CEX-Ward's dataset. To address this potential limitation, we match the auto manufacturers in the CEX to the confidential Census of Manufactures and LFTTD. These Census dataset allow us to measure both direct and indirect import shares.

[15] The data offer comprehensive coverage of at least food and beverages consumed at home, which represent 24% of expenditures on goods in the IO table. In the Nielsen data those categories constitute 72% of expenditures, with 24%/0.72 $\approx$ 33%.

Direct imports are defined as the ratio of imports of assembled cars in LFTTD to the value of car shipments from the Census of Manufactures, while indirect imports have imports of car parts in the numerator.[16]

3 Import Shares Across the Income Distribution

In this section, we measure differences in import shares across income and education groups, first across industries and then within consumer packaged goods and motor vehicles. At all levels of aggregation, we find that the import shares are similar across groups, implying that the expenditure channel of trade is distributionally neutral.

3.1 Imports Shares with Industry-Level Data

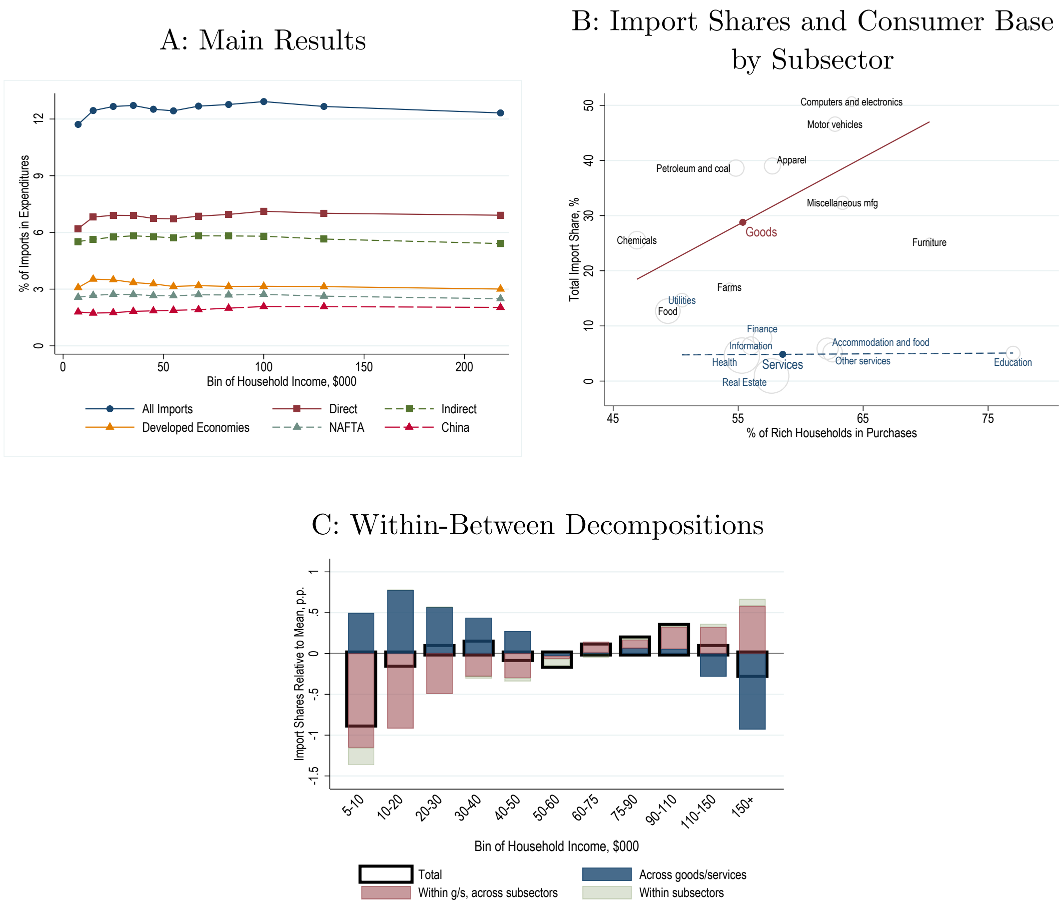
Panel A of Figure 1 reports the import shares of expenditures across the income distribution, for overall imports and for several decompositions, using industry-level data from the CEX linked to the IO table. It shows little variation in the total import share around the national average of 12.6%. For example, the import share is 11.7% for households with annual earnings below $10k a year, compared with 12.4% for households earning $50–60k, 12.9% for those earning $90-110k, and 12.3% for those earning above $150k. The panel also shows that the import shares remain flat across the income distribution when considering various subsets of imports: direct (via imported final goods) and indirect (via imported intermediate inputs), as well as for imports from China, NAFTA, and developed economies.

The small heterogeneity in import shares across income groups results from two offsetting patterns. On the one hand, lower-income groups tend to consume more goods, which are more traded, and less services, suggesting a "pro-poor" expenditure channel.[17] On the other hand, within goods higher-income groups purchase products with higher import shares. Panel B of Figure 1 shows these offsetting forces by grouping all industries into 39 subsectors and plotting their import shares against the fraction of purchases by "rich" households (defined as those earning above $60k; the

[16] A downside of the CEX-Census sample is that we have to aggregate the data from brands to firms, overlooking the heterogeneity of consumption patterns and import shares across different brands within the same firm. For this reason, our main analysis is based on the CEX-Ward's sample.

[17] The average share of imports (direct and indirect) is 28.8% for goods and only 4.9% for services. See Supplementary Figure S1 for how the spending share on goods varies with income.

Figure 1: Import Shares by Household Income Bin, CEX-IO Data



Notes: The binned scatterplots in Panel A group CEX panelists into 11 bins by household income before tax. Using the merged CEX-IO sample, this panel reports the average import share in expenditures of each bin, as well as its components arising from direct or indirect imports separately and for selected import origins. The 34 developed economies are OECD members, excluding NAFTA countries (Mexico and Canada), plus Taiwan and Singapore. In Panel B, each circle corresponds to a subsector from Supplementary Table S2; the circle size indicates final spending and subsectors that account for less than 3% of the sectoral expenditure are not shown. The x-axis shows the fraction of consumers with income above $60k in final purchases in the industry, while the y-axis reports the average import share of the subsector. Panel C decomposes the differences in imports shares across the income distribution (as in Panel A, with the aggregate share normalized to zero), isolating differences arising at different levels, via equation (3).

patterns are the same with other thresholds). There is a strong positive association for goods: subsectors with a high import share, such as Computers and Electronics, are purchased disproportionately more by high-income consumers, while subsectors without much imports, such as Food, are purchased relatively more by low-income groups.

Panel C of Figure 1 quantifies these offsetting forces using the decomposition for import shares (compared with the representative consumer) at different levels of industry aggregation, as in equation (3). It shows that if consumption baskets of different income groups varied only by the share of goods vs. services, but were identical within each sector, the import spending share for households making less than \$10k would have been 0.5p.p. higher than average, and 0.9p.p. smaller than the average for households making above \$150k. Differences in consumption baskets within goods and services offset this pattern, primarily due to the composition of subsectors (rather than of detailed industries within subsectors).

In sum, considering spending patterns across 170 categories of final consumption defined by industries, we have shown that consumers at different income levels have similar spending shares on imports, whether overall or from specific trading partners.[18] Our analysis so far could suffer from aggregation bias: for instance, it could be the case that low-income groups consume a larger fraction of imported varieties *within* industries, as in the structural analysis of Fajgelbaum and Khandelwal (2016). We now turn to this question and provide evidence that there is no such pattern for consumer packaged goods and motor vehicles.

3.2 Import Shares within Consumer Packaged Goods

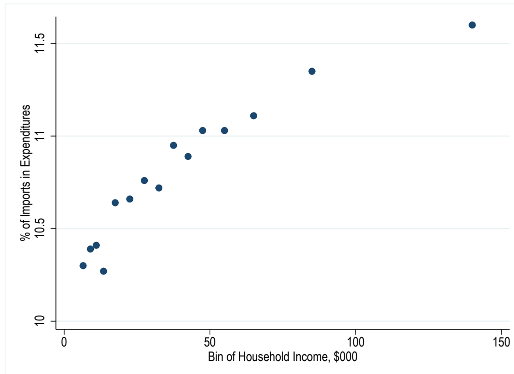
To examine within-industry spending on imports for consumer packaged goods, we use the linked Nielsen-Census database. We find that richer consumers buy relatively more imports, except from China; but the differences are small as a fraction of average import shares.

Figure 2 reports import shares by consumer income bin. Panel A shows the overall imports shares within consumer packaged goods, which increase monotonically across

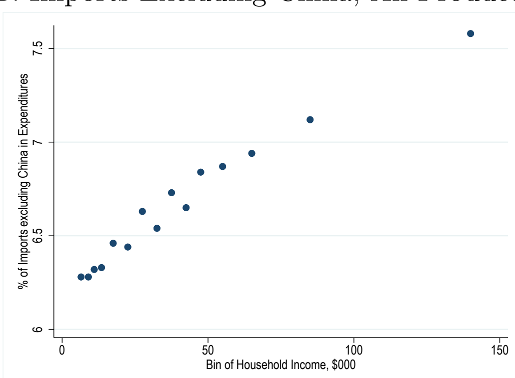
[18]Since spending shares are flat but richer households have higher expenditures, the dollar amount spent on imports increases with income, as reported in Supplementary Figure S2. Therefore, in absolute dollar value, the expenditure channel favors richer households.

Figure 2: Import Shares within Consumer Packaged Goods
by Household Income Bin, Nielsen-Census Sample

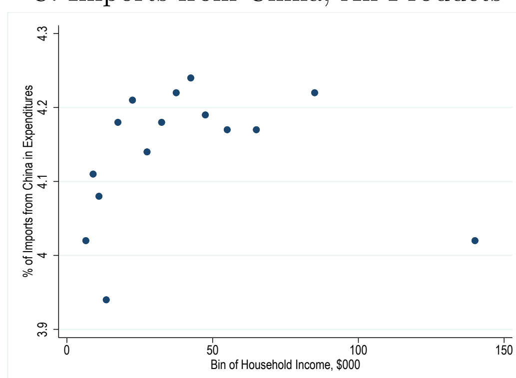
A: All Imports



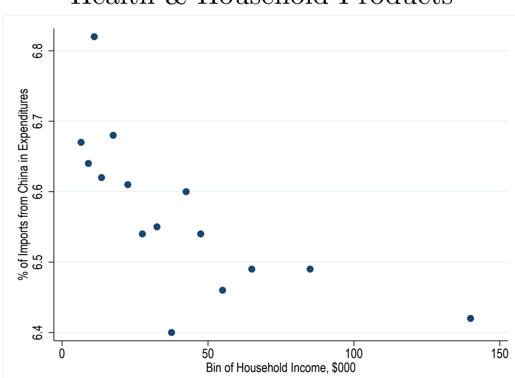
B: Imports Excluding China, All Products



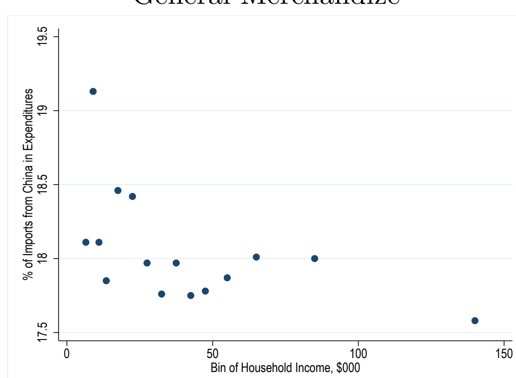
C: Imports from China, All Products



D: Imports from China,
Health & Household Products



E: Imports from China,
General Merchandize



Notes: These binned scatterplots group Nielsen panelists into 15 bins by household income. They report the average share of imports in the spending of each bin, computed using the merged Nielsen-Census sample. Panel A accounts for all imports, while Panel B excludes imports from China. The other panels measure imports from China only: for all product classes together (Panel C), Health and Household products (Panel D), and General Merchandize (Panel E).

Table 1: Within-Between Decompositions for Import Shares, Nielsen-Census Sample

	All Imports (1)	Imports Excluding China (2)	Imports From China (3)
All households, %	11.10	6.95	4.15
Households earning above \$60k, %	11.42	7.30	4.12
Households earning below \$60k, %	10.79	6.62	4.17
Above minus below, p.p.	+0.63	+0.68	-0.05
→ Within IO industries	+0.38	+0.47	-0.09
→ Within product modules	+0.24	+0.38	-0.13

Notes: This table reports the fraction of imports in expenditure on consumer packaged goods for households with annual earnings above or below \$60k, using the merged Nielsen-Census sample. Imports are proxied by the share of total imports in firm sales, and firms are weighted by the square-root of Nielsen sales. The "within" components of differences in import shares are shown for 6-digit IO industries and for Nielsen product modules, according to equation (3).

the income distribution, from 10.3% at the bottom to 11.6% at the top, compared with an average of 11.1%. Next, we investigate potential differences across trading partners. Considering imports from all countries except China in Panel B, we find that import shares still increase monotonically with income, from 6.3% for the very poor to 7.6% for the very rich.

In Panel C, the relationship between the share of imports from China and household income is less stark, hovering non-monotonically between 3.9% and 4.2%. In panels D and E, we investigate this relationship by product class. For health and household products alone, shown in Panel D, the fraction of imports from China falls with income from 6.8% to 6.4%. For general merchandize in Panel E, import shares fall from around 19.1% to 17.6%. The overall pattern of non-monotonic import shares from China stems from compositional differences across product classes (e.g., higher income groups buy relatively more general merchandize than food).

Table 1 analyzes differences in import shares arising at different levels of product aggregation, focusing on the difference between households earning above or below \$60k per year. Column 1 reports that import shares are higher for richer households, at 11.4% for those earning above \$60k versus 10.8% for those earning below. The "pro-rich" difference of 0.63 percentage points (henceforth p.p.) is equal to 5.7% of the average import share. Using equation (3), we assess whether this difference in import shares arises within or across the 71 IO industries covered by the Nielsen data and the 1,165 detailed product modules. This decomposition helps avoid double-counting, given that the "across" heterogeneity arising from IO industries was accounted for in Section 3.1. We find that, out of the 0.63p.p. difference in overall import shares between rich and poor consumers, the majority (0.38p.p.) arises within IO industry groups. Moreover, this decomposition provides an anatomy of spending on imports: we find that a substantial part of the difference in import shares (0.24p.p.) arises within product modules, i.e. at a high level of disaggregation. The results are similar for imports excluding China (Column 2), while differences are weak for imports from China regardless of the aggregation level (Column 3).

Product quality may be a natural mechanism for these relationships between imports and income. Richer consumers may value quality more, and richer countries may specialize in higher-quality products (e.g., Fajgelbaum et al. (2011)). We provide support for this mechanism empirically by proxying for quality with detailed barcode-level prices, reported in Nielsen. We convert prices into comparable units within product modules, e.g. per ounce of soda rather than per bottle, and split the distribution of prices within the module into deciles.

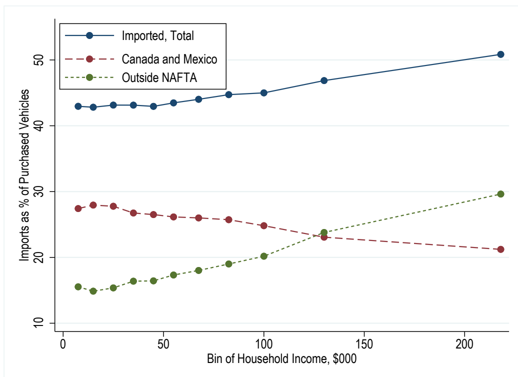
Supplementary Figure S3 shows average import shares across the distribution of prices. Consistent with quality differentiation, products in the top price deciles of their modules tend to have more imports from countries other than China, with most of the effect coming from developed countries (Panels A and B, respectively). Conversely, imports from China in the Health and Household product class are substantially more prevalent at the bottom of the price distribution (Panel C).[19]

Overall, we find that higher-income households buy more imports, in particular from countries other than China, consistent with differences in product quality. But the differences in import shares are relatively small, confirming the finding of a distributionally neutral expenditure channel.

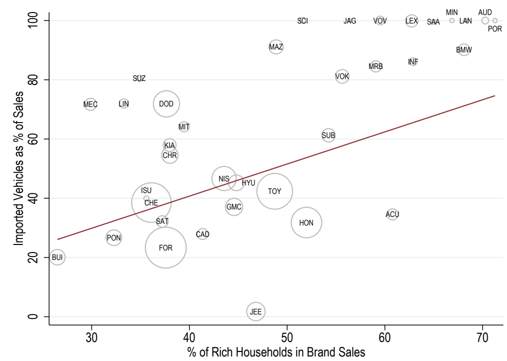
[19] This pattern is not present for imports from China within General Merchandize (Panel D), because differences in spending across consumer groups are weaker in that product class.

Figure 3: Import Shares within Motor Vehicles by Household Income, CEX-Ward's Data

A: Main results



B: Import Shares and Consumer Base across Vehicle Brands



Notes: Panel A splits motor vehicle purchases in the CEX into 11 bins by the owner's household income. Each vehicle in the data is assigned a probability of being imported, overall or specifically from NAFTA, based on the average import share of the car brand in the Ward's data. In Panel B, each circle corresponds to a vehicle brand (see Supplementary Table S3 for the brand codes). The size of each circle indicates the number of purchases in the CEX data; brands that account for less than 100 purchases are not shown. The x-axis shows the fraction of vehicle owners with income above $60k, while the y-axis reports the average import share of the brand.

3.3 Import Shares within Motor Vehicles

The motor vehicles industry differs substantially from consumer packaged goods, with a much higher import share overall and a different composition of origin countries (see Supplementary Table S1). Studying motor vehicles thus provides complementary evidence on the potential within-industry differences in import shares across the income distribution. Using the CEX-Ward's and CEX-Census linked datasets, we find that rich consumers have a slightly higher share of imports for car purchases; the difference is substantial for specific trade partners.

In Figure 3 we examine spending shares on vehicles assembled outside of the United States, leaving aside indirect imports (i.e., imported parts of domestically produced vehicles), using the CEX-Ward's dataset. Panel A shows that import shares are nearly flat, around 44%, for most of the income distribution. Import shares increase at the top, reaching 50.8% for those earning over $150k.

The overall pattern hides substantial heterogeneity by country of origin. Vehicles assembled in Canada and Mexico account for 27% of total purchases at the bottom of the income distribution, compared with 21% at the top. In contrast, there is a steep positive relationship for vehicles assembled in foreign countries outside NAFTA—mostly in developed countries. Imports shares excluding NAFTA double across the income distribution: from around 15% at the bottom to 30% at the top.

Panel B of Figure 3 unpacks these findings by showing which brands drive the effect. We plot the import share of a brand against the fraction of its sales to households with annual earnings above $60k. Two clusters of brands become apparent. High-end foreign brands tend to sell to high-income households, e.g., Lexus, Porsche, and Mercedes-Benz. Brands selling to less affluent consumers are almost all domestic (e.g., Chevrolet, Buick, and Dodge), although their import shares are still positive due to assembly in Mexico and Canada. These within-industry patterns are again consistent with the idea of quality specialization across countries.

Supplementary Figure S4 provides additional decompositions for the overall import shares. It shows that differences in import spending exist for cars but are very small for light trucks. The results are robust to considering vehicles purchased new or used separately.

Finally, since the CEX-Ward's data do not account for imported intermediate inputs, we use the linked CEX-Census sample to address this limitation. We find that accounting for indirect imports slightly mutes the differences in import shares across income groups. Because data confidentiality does not allow us to show individual firms, as in Figure 3, we report the results via regressions at the firm (i.e., car manufacturer) level. We first regress a firm's direct import share on the average income percentile of households purchasing its cars, weighting by the number of cars sold. We then compare the coefficient to a similar regression with the total import share as the outcome. Table 2 reports the results, separately for new and used cars. In both cases, the coefficient for total imports is slightly smaller, and the difference is not statistically significant. These results indicate that rich consumers spend slightly less on indirect import of vehicles (as they buy fewer domestic models) but this offsetting effect is very small, which confirms our baseline estimates for direct imports.

Taking stock, several lessons can be drawn from the patterns we found for consumer packaged goods and motor vehicles. There are some differences in import shares from specific trade patterns across the income distribution, in line with patterns of

Table 2: Household Income and Direct and Indirect Imports of Cars

	Imports as % of Car Sales			
	New Cars		Used Cars	
	Direct (1)	Direct & Indirect (2)	Direct (3)	Direct & Indirect (4)
Average percentile of household income	1.955 (0.538)	1.829 (0.495)	2.546 (0.474)	2.389 (0.414)
N firms	20	20	20	20

Notes: This level of observation in this table is a car manufacturer. The dependent variables in the Ordinary Least Squares regressions are the manufacturer-level shares of imports of assembled cars ("Direct") or of both assembled cars and imported inputs ("Direct & Indirect") in the value of car sales. The independent variable is the average percentile of household income in the CEX sample of car purchases, computed separately for new cars in Columns 1 and 2 and used cars in Columns 3 and 4. Each regression is weighted by the number of purchases recorded in the CEX. The sample size is rounded to the nearest 10 to protect confidentiality. Robust standard errors are shown in parentheses.

quality specialization. These partner-specific differences tend to offset each other: between China and developed countries for consumer packaged goods, and between NAFTA and developed countries for motor vehicles. When imports from all trade partners are considered together, import shares are slightly higher for high-income consumers within the industries we studied. Combining this result with our finding of no heterogeneity in import shares at the level of detailed industries in Section 3.1, we conclude that the distributional effects through the expenditure channel are modest and, if anything, favor higher-income households.

3.4 Extensions

We conclude this section by reporting additional results documenting the heterogeneity in import shares across other socio-demographic groups, notably education groups, as well as its evolution over a long time period. We find weak differences in import shares to be a very robust pattern.

Import shares across education groups. We report the import shares for households with and without a college degree using all three datasets in Supplementary

Table S4. Differences are small: import shares measured at the industry level are 0.6p.p. (i.e., 5.1% of the average import share) lower for college-educated consumers, compared to those without a college degree. Within-industry differences have the opposite sign. Within consumer packaged goods, the import share is 0.6p.p. larger for college-educated households (or 5.4% of the average).[20] The difference is larger for motor vehicles, where the import share is 5.1p.p. higher for college graduates (or 11.4% of the average).

The offsetting pattern of across- and within-industry differences applies to specific trade partners as well. Although college graduates purchase relatively *more* from industries with higher shares of imports from China, they spend *less* on Chinese imports within consumer packaged goods. Conversely, they purchase *less* from industries with imports from developed economies but *more* on imports from those countries for consumer packaged goods and especially for motor vehicles.

Import shares for other socio-demographic groups. Using industry-level data, Supplementary Figure S5 shows that the fraction of spending on imports is also similar across other socio-demographic groups. We consider more detailed education groups, age groups, households who live in the four Census regions, in the states that voted for Hillary Clinton vs. Donald Trump in the 2016 election, households who are homeowners or not, or who differ by household size.

Stability of import share differences over time. Supplementary Figure S6 shows the stability of the patterns across income and education groups over time, using available panel data on 71 more aggregated industries. Each year between 2002 and 2015, the spending shares on imports were very similar for these groups.

4 Comparison with Parametric Approaches

In this section, we reconcile our results with the very strong pro-poor distributional effects from trade found in the study of the expenditure channel by Fajgelbaum and Khandelwal (2016, henceforth FK). After reviewing the patterns FK obtained,

[20] Supplementary Table S5 shows that this difference likely arises from direct, rather than indirect, imports. We do not classify products into final and intermediate but instead consider the main activity of the firm that registered the barcode. We find that most of the difference in import shares across education groups, both overall and for Chinese imports in health and household products, arises from imports registered by wholesalers, which are likely imports of final products.

we present a theoretical argument explaining that the AIDS demand system they employ tends to mechanically generate such a pro-poor expenditure channel. We then estimate an alternative demand system that does not have this mechanical feature and find that the expenditure channel is small, consistent with the evidence presented earlier. We leave various details to Appendix B.

FK use widely available bilateral trade data for 40 countries and 35 industries. For each country they observe spending shares on imported products on average, but not at different points of the income distribution. Therefore, they infer these missing data structurally, by estimating a non-homothetic demand system. Specifically, they employ the Almost-Ideal Demand System in which each variety, defined by a pair of industry j and producing country c, is characterized by an income semi-elasticity parameter β_{jc}. They estimate these parameters using a non-homothetic gravity equation, assuming that all goods are used for final consumption only.

They find that the gains from trade relative to autarky are larger for low-income consumers in all countries, and by over an order of magnitude in the United States. For example, the gains equal 65.6% at the 10th percentile of the U.S. income distribution compared with 2.5% at the 90th; the interquartile range is also large, from 51.2% at the 25th percentile to 14.1% at the 75th. In contrast, we found that the expenditure channel of trade is distributionally neutral, to a first order. What explains these differences?

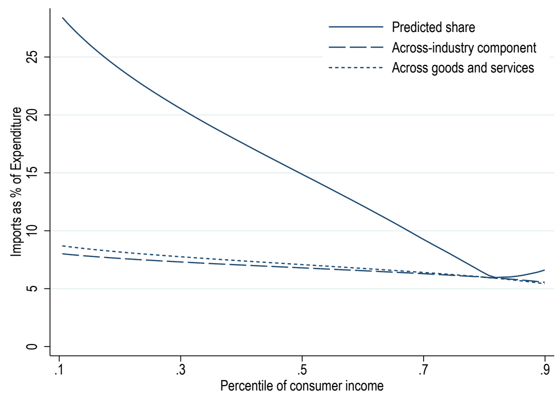
To understand the source of the discrepancy with our results, it is instructive to first examine the import spending shares inferred by the AIDS demand system with the parameters estimated by FK. In their model, like in our Section 2.1, import shares are directly informative about the effects of small shocks.[21] We replicate their estimates and extract the imputed spending shares for the U.S., which are shown in Panel A of Figure 4. The figure indicates strong heterogeneity across income groups, e.g. at 21.9% for the 25th percentile and only 8.1% at the 75th.

Applying the within-between decomposition of equation (3), Panel A further shows that most of the imputed differences in import shares across the income distribution occur *within* industries. That is, according to AIDS, the poor tend to buy much more foreign varieties when they purchase from the same industry as the rich. In contrast, only around one tenth of the overall difference in imports shares (comparing the 25th

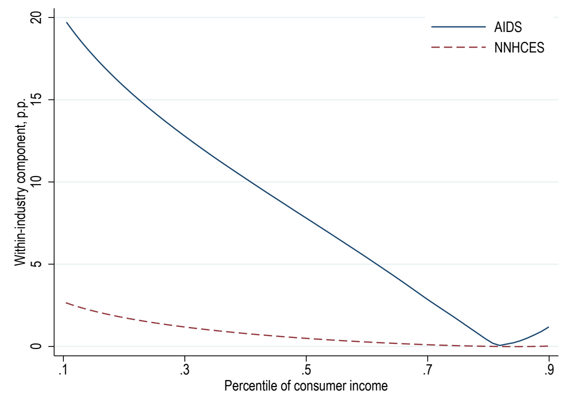
[21] We have verified that our first-order approximation is accurate for measuring the gains from a 5% reduction in foreign tariffs, reported in Section V.E of FK.

Figure 4: U.S. Import Shares by Income Percentile
Estimated with Parametric Approaches

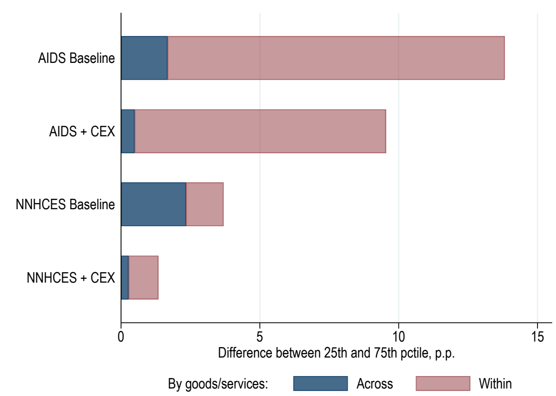
A: Imports Shares across Income Groups: AIDS
Estimated by Fajgelbaum and Khandelwal (2016)



B: Within-Industry Differences in
Import Shares: NNHCES vs. AIDS



C: Import Share Heterogeneity
under Alternative Estimation Strategies



Notes: This figure reports statistics on import shares across the U.S. income distribution, using international trade data to estimate income elasticities in two demand systems: AIDS (with parameters from Fajgelbaum and Khandelwal (2016, FK)) and NNHCES. Panel A shows the import shares predicted by AIDS. It also decomposes them into different aggregation levels via equation (3), but adding back the import share of the representative agent (defined as in FK). Panel B compares the within-industry component of the difference in import shares relative to the representative agent between the two demand systems. Panel C reports the predicted gap in import shares between the 75th and 25th income percentiles for different estimation methods, as well as its component arising between goods and services. While bars 1 and 3 use the baseline versions of AIDS and NNHCES, respectively, bars 2 and 4 use constrained estimation aimed to match the income elasticity of goods with the CEX estimates.

and 75th percentiles) arises across industries, i.e. because richer households buy more from industries with lower average import shares, such as service industries.[22]

Large within-industry heterogeneity in import shares is found even in the industries most comparable to those for which we presented evidence from micro data. Supplementary Figure S7 shows the imports shares across the income distribution within food and motor vehicles (Panels A and B), according to the imputation of FK. For food, the demand system imputes the spending share on imports to be 44.7% at the 25th percentile and only 14.0% at the 75th, while we found essentially no heterogeneity using the Nielsen-Census data. Similarly, for motor vehicles the predicted import shares are 46.5% at the 25th percentile and 34.0% at the 75th, while our CEX-Ward's data indicate the opposite pattern: weakly higher shares of imported cars for richer households. There is thus a striking contrast between the import shares imputed by AIDS and our data.

This large within-industry heterogeneity in import shares proves to be an intrinsic feature of the AIDS demand system used by FK, which mechanically results in a large pro-poor expenditure channel. We first present the theoretical mechanism at play and then show that the expenditure channel becomes close to distributionally neutral when estimating an alternative demand system immune to this issue. Specifically, the strong pro-poor expenditure channel in FK stems from the conjunction of three features: constant income semi-elasticities imposed by AIDS, home bias, and income-inelastic tradables.

Identical AIDS preferences across countries, as assumed by FK, imply that for any variety jc the income *semi*-elasticity of expenditure shares s^n_{jc} is the same in all purchasing countries n (and for all consumers): $\frac{\partial s^n_{jc}(p_n,w)}{\partial \log w} \equiv \beta_{jc}$, where w is consumer income and p_n is the price vector in n. As an immediate consequence, the income *elasticity* of the expenditure share is closer to zero when the share is higher: $\frac{\partial \log s^n_{jc}(p_n,w)}{\partial \log w} = \frac{\beta_{jc}}{s^n_{jc}(p_n,w)}$. This relationship is important because it interacts with home bias: spending shares on a given variety are generally larger in the country where it is produced. As a result, spending shares are always more income-sensitive abroad than at home. This could in principle make them either more income-elastic or more income-inelastic, depending on the sign of β_{jc}. However, tradables tend to be income-inelastic, and thus *foreign* tradables are particularly income-inelastic under

[22]The panel also shows that this across-industry component primarily results from the fact that the rich purchase relatively more services, which are less tradable than goods.

AIDS. This mechanically makes the share of imports in spending on tradables quickly decline with income.[23]

Next, we assess the quantitative importance of this mechanical property of AIDS and whether it can explain the discrepancy with our Section 3 results. Using the data from FK, we estimate an alternative demand system which is not affected by the issue described above: nested non-homothetic CES (NNHCES), introduced in Appendix B.2 building on Comin et al. (2021). This demand system is as flexible as AIDS in having a free Engel curve parameter per variety, which we label φ_{jc}. However, the income elasticity is not mechanically linked to the spending share: if two country-specific varieties in the same industry have the same value of φ, then in every country they are guaranteed to have equal income elasticities. This demand system therefore allows for, but does not mechanically generate, within-industry differences in import shares.[24] We estimate the NNHCES parameters by combining a gravity approach similar to that of FK with the non-homothetic CES estimation procedure of Comin et al. (2021), as described in the Appendix. We then compute the import shares by consumer income for the U.S. and apply the within-between decomposition.

In line with the theoretical argument above, Panel B of Figure 4 shows that within-industry differences in import shares across the U.S. income distribution, which are large with AIDS, become modest with NNHCES. Specifically, the difference between the 25th and 75th percentiles is 12.1p.p. for AIDS but nine times smaller, at 1.35p.p., with NNHCES. These results illustrate how AIDS mechanically generates large differences in import shares, which are significantly attenuated with an alternative demand system like NNHCES.

To assess whether the expenditure channel is close to distributionally neutral with NNHCES, we must also take into account the across-industry differences in import shares implied by that demand system. Using international trade data to estimate the income elasticity of goods relative to services, which drives the across-industry component, turns out to be challenging, since services are largely non-traded. In the baseline estimates of FK, for example, goods are strongly income-inelastic (see Panel C of our Supplementary Figure S7 for U.S. consumers), much more so than

[23] In Appendix B.2, we provide formal derivations for this argument. In particular, we show that there is no offsetting pattern within income-elastic services, because spending shares of foreign services cannot fall below zero.

[24] More generally, we show that, among varieties in the same industry, higher φ_{jc} means higher income elasticity in every country; see equation (23) in the Appendix.

implied by the observed differences in expenditure shares on goods across the income distribution in the CEX (Supplementary Figure S1). This point was noted by FK (Section V.D), who then re-estimate their AIDS demand system under the constraint that the average income elasticity for goods should be consistent with the expenditure patterns in the CEX for the U.S.

Emulating the approach taken by FK, we re-estimate NNHCES with a constraint ensuring that the income elasticity of the goods sector for the U.S. matches the corresponding elasticity in the CEX. This approach, described in detail in the Appendix, keeps the parameters driving the within-industry component identical to Panel B of Figure 4 by design, but disciplines the across component with the CEX.

Panel C of Figure 4 reports the findings with this approach, in comparison to the ones discussed above. The first bar replicates the baseline results of FK using AIDS, which imply a 13.8p.p. higher import share at the 25th percentile of the U.S. income distribution compared to the 75th. The gap shrinks to 9.5p.p. with FK's estimation of AIDS constrained by the CEX (second bar): although the component across goods and services becomes much smaller, the overall difference in import shares remains large due to the within component inherent to AIDS. The third and fourth bars present the results for NNHCES. The across component is sizable in the baseline (row three), but falls when estimation is constrained by the CEX in row four. The overall difference in import shares between the 25th and 75th percentiles becomes only 1.3p.p. there.

These results show that the structural approach of FK can be reconciled with direct measurement. When using a demand system like NNHCES, which does not inherit the mechanical features of the AIDS demand system of FK, the expenditure channel of trade turns out to be small. More broadly, this analysis shows that the choice of the demand system can have a large quantitative impact on the estimated expenditure channel, highlighting the value of a direct measurement approach.[25]

[25]We proposed a simple refinement for the structural approach of FK, using NNHCES instead of AIDS to avoid a mechanical tendency to find a pro-poor expenditure channel. It seems fruitful to investigate other potential refinements in future work, such as: (i) using expenditure microdata from multiple countries for estimation; (ii) allowing for heterogeneous preferences across countries; (iii) introducing additional gravity controls to mitigate the limitation that prices are not observed; and (iv) deriving standard errors to assess how precise estimates of the imputed import shares are, especially for extreme (high or low) income levels.

5 The Distributional Effects of Trade Shocks in General Equilibrium

In this section, we first characterize theoretically the distributional effects of counterfactual trade shocks in general equilibrium (with details and proofs relegated to Appendix C). We then calibrate the relevant elasticity parameters, document the exposure patterns governing the characterization, and perform counterfactual analysis.

5.1 An Exposure-Based Characterization of Changes in Factor Prices

We consider a standard setting for the product market, labor market, and the domestic production function. Products $\omega = (j, c)$ are defined as pairs of industry $j = 1, \ldots, J$ and country of origin c, as in multi-sector versions of Armington (1969). Consumer preferences across industries are unrestricted; preferences over varieties within each industry are CES, with the same parameters for both final and intermediate demand. These preferences imply industry-level gravity, with trade elasticities denoted $\xi_j - 1$.[26]

In the labor market, workers are exogenously grouped into types $i = 1, \ldots, I$ with wages w_i per efficiency unit. Workers of the same type supply labor inelastically and can be endowed with different efficiency units, capturing within-group income inequality.[27] Type-i workers are freely mobile within a set of industries $\mathcal{J}_i$, but are not employed outside it. This formulation allows for a scenario with no mobility across industries (i.e., i are industry groups and $\mathcal{J}_i = \{i\}$), as well as a scenario in which i corresponds to education groups freely mobile across all domestic industries, as in our calibrations below.[28]

[26]For tractability, we follow, e.g., Caron et al. (2014) in allowing for non-homothetic utility across industries but not within. This specification is in line with our finding that import spending shares within industries do not vary systematically across income groups, and it delivers the standard proportionality assumption embedded in country-specific IO tables. Non-homothetic demand within industries, for example via NNHCES, can be accommodated and would yield a characterization similar to Proposition 2 below.

[27]The theory allows for unrestricted factor types, such as different types of workers or capital investments. Empirically, we will focus on worker groups in the main analysis and consider capital in a robustness check.

[28]This approach can be generalized to a finite elasticity of labor supply in each industry via a Roy model; see Appendix A.4 in our working paper (Borusyak and Jaravel 2018) and Galle et al. (2020).

Domestic production in industry j combines primary factors L_i^j with composite inputs Q_ℓ^j from all industries ℓ. We assume a Cobb-Douglas production function in terms of value added and intermediate inputs, $Q_{jH} = F_j^{VA}\left(L_1^j, \ldots, L_I^j\right)^{1-\beta_j} \cdot \Pi_{\ell=1}^{J}\left(Q_\ell^j\right)^{\beta_\ell^j}$, with $\sum_\ell \beta_\ell^j = \beta_j$, but allow for any homothetic value-added aggregator F_j^{VA}. The Cobb-Douglas assumption for intermediate inputs is standard (e.g. Acemoglu et al. 2012; Caliendo and Parro 2015) and consistent with the stability of input shares in the U.S. IO table over time.

We consider how domestic factor prices adjust in general equilibrium (GE) following a bilateral reduction in trade costs between Home and some country (or set of countries) c in all industries, $d\log\tau < 0$. Since our detailed data only cover the U.S., we rule out changes in relative factor prices abroad by imposing:

Assumption 4 (Foreign numeraire)**.** *For every industry and foreign country, exports to Home are a small fraction of sales, and imports from Home are a small fraction of industry absorption.*

Assumption 4 implies that relative product demand and price indices abroad do not significantly move after the trade shock with Home. Under Assumption 4, we can disregard both that the Home economy may be embedded into GVCs (as with our Assumption 3) and that relative foreign factor prices (across or within countries) may change after the shock. We thus take all foreign prices as the single numeraire.[29]

Finally, we allow for a trade imbalance in the domestic economy assuming, as in Costinot and Rodríguez-Clare (2015), that it is fixed in proportion to Home's GDP. Specifically, we assume that every consumer spends the same exogenous multiple of their income.

To state our main result, we introduce some notation. On the import side, we define IP_{jc} as the share of imports from c in domestic absorption of j at the initial equilibrium (with IP_j for the total import penetration); $\widetilde{IP}_{jc}$ is the share of imports in industry absorption both directly and indirectly via IO linkages. The share of inputs imported from c, both directly and indirectly, in the domestic cost structure is denoted

[29]In the quantitative analysis, we focus on a uniform change in trade costs with all countries, where the assumption of fixed relative factor prices outside Home appears plausible. Indeed, the U.S. economy accounts for a small share of sales and absorption in the rest of the world. While the U.S. accounts for a substantial fraction of world GDP, exports from the U.S. constitute only 3.9% of absorption in other countries according to the World Development Indicators database for 2007. Exports to the U.S. similarly account for only 5.5% of foreign production.

$\widetilde{IP}_{jc}^{\text{Int}}$, as in Section 2.1. On the export side, $ExSh_{jc}$ denotes the share of exports to country c in j's domestic output. $DomSalesSh_j$ denotes the share of domestic sales (both final and intermediate) in j's total sales. The share of final domestic customers in total sales is DFS_j, and $\mu_{x|j}$ are the shares of sales to consumers with income x in j's final sales. We characterize domestic final demand of consumers with income x by the income elasticity ψ_{xj} and the own- and cross-price elasticities ε_{xjk} measuring the response of j's expenditure *share* to industry k's price index change. Then, we have (see Appendix C.1 for the details and proof):

Proposition 2. *Suppose Assumptions 1 and 4 hold. Then after a uniform reduction in bilateral trade costs with country c, changes in wages $w = (w_1, \ldots, w_I)$ satisfy*

$$\frac{d\log w}{-d\log\tau} = \underbrace{\tilde{\boldsymbol{G}}}_{\substack{\text{inverse labor demand}\\ \text{elasticity matrix}}} \cdot \underbrace{\boldsymbol{E}\tilde{\boldsymbol{D}}\eta}_{\substack{\text{labor demand}\\ \text{response}}}. \tag{4}$$

Here η is a $J \times 1$ vector of direct industry exposure to the shock via several channels:

$$\eta_j = (\xi_j - 1)\Big[\underbrace{ExSh_{jc}}_{\text{export effect}} - \underbrace{IP_{jc}\cdot DomSalesSh_j}_{\text{import competition effect}} + \underbrace{\widetilde{IP}_{jc}^{Int}\cdot(ExSh_j + IP_j\cdot DomSalesSh_j)}_{\text{intermediate input effect}}\Big]$$

$$+ DFS_j \cdot \sum_x \mu_{x|j}\Big[\underbrace{(\psi_{xj}-1)\,ImpSh_c^x}_{\text{income effect}} - \sum_{k=1}^{J}\underbrace{\varepsilon_{xjk}\left(\widetilde{IP}_{kc} - ImpSh_c^x\right)}_{\text{substitution effects}}\Big]. \tag{5}$$

The "IO adjustment" $J\times J$ matrix $\tilde{\boldsymbol{D}}$ is such that $\left(\tilde{\boldsymbol{D}}\eta\right)_j$ is the sum of direct industry j exposure η_j and indirect exposure in industries downstream from j. The "payroll composition" $I\times J$ matrix $\boldsymbol{E}$ captures the shares of industries j in type i payroll, such that $\boldsymbol{E}\tilde{\boldsymbol{D}}\eta$ measures the payroll-weighted average shock exposure by labor type. Finally, $\tilde{\boldsymbol{G}}$ is the (negative of the) $I\times I$ inverse matrix of macro labor demand elasticities with respect to w, given by (47) in the Appendix.

The intuition behind equation (4) is that, with fixed labor supply, trade shocks affect wages via shifts in labor demand. Shifts in labor demand arise from product demand in industries which employ each type of labor. The novel characterization in equation (5) shows that the product demand response to a small shock can be decomposed into several channels, each driven by observable exposure measures scaled by corresponding elasticities, which we discuss in turn.[30]

[30]Proposition 2 immediately extends to shocks that are not uniform across industries or affect

The first two terms in (5) show the *export* and *import competition effects.* As export trade costs fall, export demand grows according to the trade elasticity $\xi_j - 1$, contributing to industry labor demand growth in proportion to the export share $ExSh_{jc}$. Similarly, falling import trade costs lower import prices, which drives the industry price index down in proportion to import penetration IP_{jc}. This leads to reallocation of spending between domestic and foreign varieties within each industry. Because this effect only influences domestic consumption, it is scaled by the domestic share of industry sales, $DomSalesSh_j$.[31]

The third term relates to *imported intermediate inputs.* Access to cheaper intermediate inputs makes domestic varieties more competitive, helping them gain market shares both abroad at at home. Industries are more exposed to this channel when they have a higher share of imported inputs $\widetilde{IP}_{jc}^{\text{Int}}$ in production costs.

The final terms are the *income and substitution effects.* Partial equilibrium welfare gains, driven by the import share $ImpSh_c^x$, lead to higher spending on income-elastic industries (those with $\psi_{xj} > 1$). Moreover, demand for a domestic industry falls if substitute industries k (those with $\varepsilon_{xjk} > 0$) become relatively cheaper, due to their above-average import share, and if complement industries have below-average import shares. Both effects only influence domestic final sales, as combining consumers of different income, hence the scaling by their shares in total sales.

Proposition 2 provides a transparent way of connecting theory to data and guides our empirical analysis, which proceeds in five steps. First, we measure each statistic of direct industry exposure to trade in (5). Second, we adjust these statistics for input-output linkages (via the $\tilde{\boldsymbol{D}}$ matrix), for example measuring the share of industry output that is exported to c not only directly but also in downstream industries. Third, we obtain labor demand shifts for each group by averaging industry exposure with using the fractions of different industries in the group's payroll (captured by the $\boldsymbol{E}$ matrix). Fourth, we translate these labor demand shifts into the general equilibrium wage changes by applying the $\tilde{\boldsymbol{G}}$ matrix. Finally, we measure the welfare

only importing or only exporting costs. We present the benchmark case for notational brevity; see Appendix S.2.7 for the general case.

[31]Unlike traditional factor content statistics, the measure of exposure to import competition in Proposition 2 is valid in the presence of international specialization. Consider an industry, such as toys, in which the U.S. has largely stopped producing. Then its factor intensity is largely irrelevant for factor domestic demand and prices. Accordingly, it does not have a sizable effect on our exposure measure, while it can have large effects on the factor content of trade (e.g. Wood 1995).

effects, $d\log\mathcal{W}$, accounting for changes in both wages and cost-of-living in general equilibrium, via equation (2).

Given $d\log\mathcal{W}$, we analyze the distributional effects of the shock, i.e. the heterogeneity in $d\log\mathcal{W}$. We decompose it into the "vertical" and "horizontal" components, i.e. the unequal effects across and within groups of initial earnings, X, using a variance decomposition:

$$\mathrm{Var}\left[d\log\mathcal{W}\right] = \underbrace{\mathrm{Var}\left[\mathbb{E}\left[d\log\mathcal{W} \mid X\right]\right]}_{\text{"vertical" distributional effects}} + \underbrace{\mathbb{E}\left[\mathrm{Var}\left[d\log\mathcal{W} \mid X\right]\right]}_{\text{"horizontal" distributional effects}} . \tag{6}$$

We further analyze the effects of the trade shock on measures of inequality, which, at the first order, arise from the vertical component only. For instance, the change in the standard deviation of log-earnings is non-zero only if the distributional effects are correlated with the initial income:[32]

$$\mathrm{SD}\left(\log X + d\log\mathcal{W}\right) - \mathrm{SD}\left(\log X\right) \approx \mathrm{Corr}\left[d\log\mathcal{W}, \log X\right] \cdot \mathrm{SD}\left(d\log\mathcal{W}\right). \tag{7}$$

We apply these results in two calibrations. To assess both vertical and horizontal distributional effects, we first consider a setting with no mobility of workers across industries. In this calibration, worker types i are defined by industries, but the results would be identical if each worker was a distinct type; we therefore refer to this setting as the "worker-level calibration." Second, to shed more light on the distributional effects that may arise across groups of ex-ante similar workers, we consider a calibration at the level of two education groups, assuming perfect mobility of each group of workers across industries.

5.2 From Theory to Data

We now take Proposition 2 to the data, combining exposure statistics with corresponding elasticities.

To measure worker exposure to trade, we augment our industry-level data from Section 2.2 (on trade shares, IO linkages, etc.) with the worker composition of each industry. We rely on the 2007 American Community Survey (ACS) to measure the payroll shares corresponding to college and non-college workers, as well as deciles of earnings; see Appendix S.2.4 on the data construction.

[32]This follows because $d\log\mathcal{W}$ has only a second-order effect on $\mathrm{Var}\left[d\log X + d\log\mathcal{W}\right]$, unless $d\log\mathcal{W}$ and $\log X$ are correlated. See Appendix C.3 for the proof.

To characterize the income effects, we estimate income elasticities for each industry using CEX data, as described in Appendix S.2.5. We ignore the possibility that they vary with income, setting $\psi_{xj} \equiv \psi_j$.

We calibrate substitution elasticities by using prevalent values from the literature and considering robustness to a range of other values.[33] We set the baseline elasticity of substitution between domestic and foreign varieties ξ_j to 3.5 in all industries, which is equivalent to a trade elasticity of $\xi_j - 1 = 2.5$. To discipline the across-industry substitution effects, we employ the nested non-homothetic CES demand system . We allow for two tiers: goods versus services, and IO industries within goods and services (see equation (49) in the Appendix). We set the elasticity of substitution between goods and services to $\rho = 0.6$, indicating complementarity in consumption, and the elasticity of substitution across industries within each sector $r \in \{\text{goods, services}\}$ to $\varepsilon_r = 2$. A calibrated NNHCES demand system implies ε_{jxk} (see equation (50)).

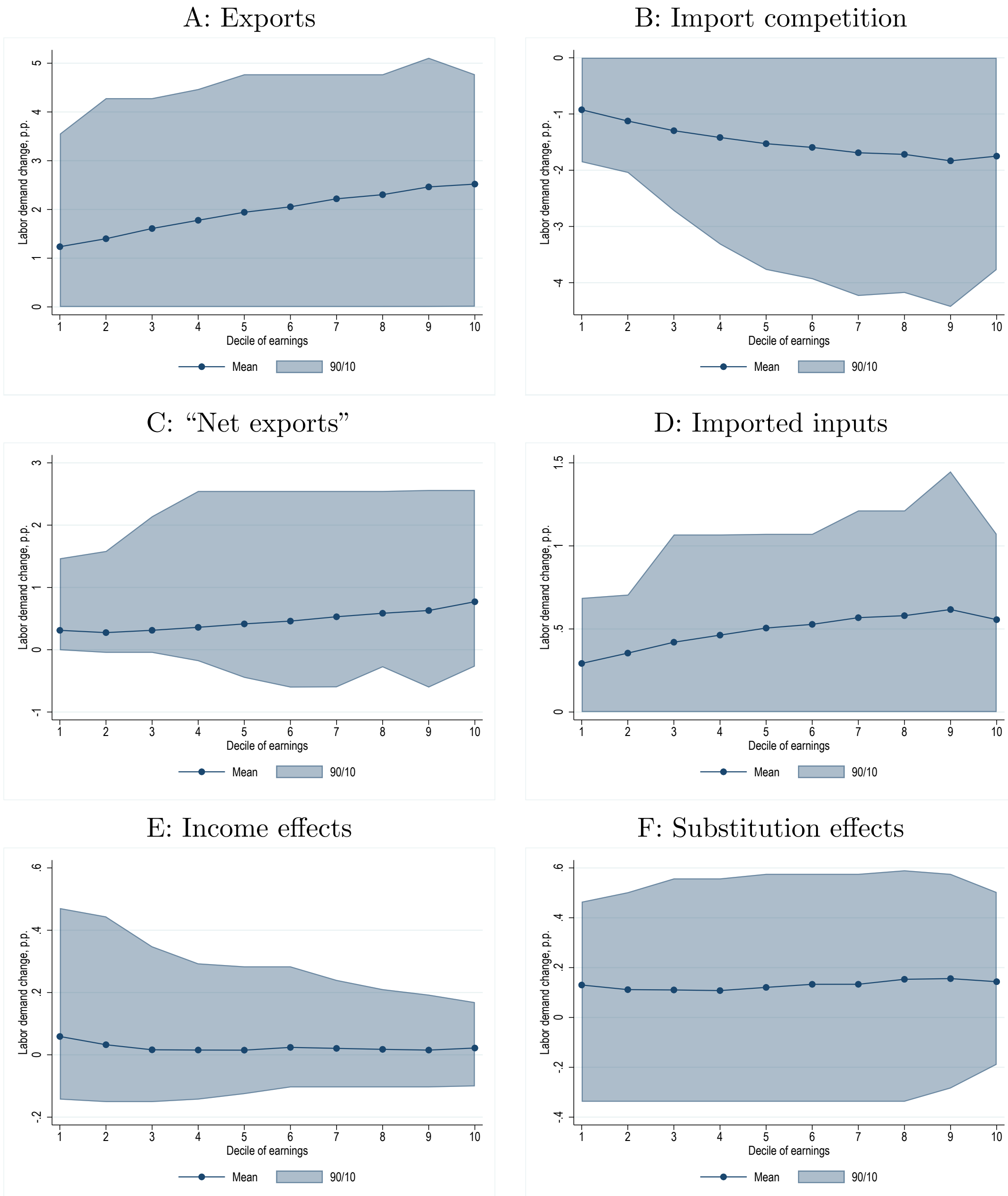
Proposition 2 finally requires us to calibrate the $\tilde{\boldsymbol{G}}$ matrix. While in general it may depend on the patterns of local labor substitution in each industry (through the F_j^{VA} functions), Appendix C.2 shows how it simplifies in the two calibrations we consider. Specifically, absent labor mobility, within-industry substitution plays no role. With free labor mobility but only two labor types, as in our analysis across education groups, labor substitution elasticities of various industries enter the $\tilde{\boldsymbol{G}}$ matrix via one composite value: the macro elasticity of labor substitution, σ_{macro}. We follow Burstein and Vogel (2017), Cravino and Sotelo (2019), and Caron et al. (2020) by calibrating the macro elasticity directly rather than aggregating it from micro estimates. For the baseline calibration we use an estimate of 1.41 obtained by Katz and Murphy (1992).

5.3 Distributional Effects: A Worker-Level Calibration

We start with the worker-level calibration. Figure 5 depicts the measures of worker exposure to trade by decile of the income distribution, showing that exposure varies primarily within deciles rather than across. Using Proposition 2, we present the five components of worker exposure, $\boldsymbol{E}\tilde{\boldsymbol{D}}\eta$, multiplying these terms by the 10% change in trade costs. The results are directly informative about the drivers of the labor demand response to trade liberalizations for different workers. For each income decile,

[33] Appendix S.2.6 discusses the literature from which we borrow these elasticities, as well as their ranges that we consider in robustness checks.

Figure 5: Worker-Level Exposure to the Labor Market Effects of Trade Shocks across the Income Distribution



Notes: This figure groups workers from the ACS data by decile of earnings and plots the channels of the labor demand response following a uniform 10% fall in trade costs. Panels A–B and D–F correspond to the five components of $\boldsymbol{E}\tilde{\boldsymbol{D}}\eta \cdot 10\%$ in Proposition 2, while Panel C shows the sum of exposures to exports and import competition. Each panel reports the average, the 10th percentile, and the 90th percentile across workers in each bin.

we report average worker exposure along with the 10th and 90th percentiles of the worker-level exposure distribution. The within-decile variation arises from different industries employing workers from the same income decile.

Panel A shows changes in labor demand resulting from the export channel after a 10% fall in trade costs. The increase in labor demand is larger for higher-income workers, ranging from about +1.2% for the average worker in the first decile to about +2.5% on average within the top decile. The change in labor demand varies substantially more across workers within deciles, with 90-10 gaps between 3.6p.p. and 5.1p.p.. Panel B reports the changes in labor demand from the import competition channel: the fall in labor demand is more pronounced for higher-income workers, with a change of about -1.8% in the top decile compared with -0.9% in the bottom decile. Heterogeneity in the labor demand effects of import competition is large within each decile, with 90-10 gaps of 1.9 to 4.4p.p.[34] On net, increases in labor demand from exposure to both export opportunities and import competition, reported in Panel C, are stronger for richer workers.This "net exports" composite channel ranges from about 0.3% on average in the bottom decile to 0.8% in the top decile, while the variation within each decile is substantial, with 90-10 gaps over 1.5p.p.

Next, Panel D shows that the increase in labor demand from the imported inputs channel is also largest in the top decile relative to the bottom (at 0.6% vs 0.3%), again with large heterogeneity within deciles shown by the 90-10 gaps of 0.7-1.5p.p. Panel E reports changes in labor demand from income effects, which are relatively flat across deciles and close to zero on average, but vary substantially within each decile, with 90-10 gaps of 0.2-0.5p.p. Similarly, Panel F shows that changes in labor demand from substitution effects are essentially flat across the distribution, with 90-10 gaps of 0.7-0.9p.p.[35]

Following Proposition 2, Panel A of Figure 6 reports the overall change in labor

[34]The finding that high-earning workers are on average more exposed to import competition contrasts with the traditional two-sector, two-factor formulation of the Heckscher-Ohlin model, in which low-paid workers are more exposed to import competition and lose from trade. Instead, our results highlight the importance of trade costs to understand the distributional effects of trade: high-earning workers are more likely to be employed in the more tradable manufacturing sector, as well as in more tradable industries within both manufacturing and services.

[35]We find that these patterns are driven primarily by the heterogeneity of worker exposure to export ratios, import penetration, cost shares of intermediate inputs, and income elasticities of their industries, rather than by IO and other adjustments from Proposition 2. We show this result in Supplementary Figure S8, which reports "raw" exposure statistics and finds patterns similar to Figure 5, both within and across income groups.

demand, combining the five channels from Figure 5. Panel A(i) shows that there is higher growth of labor demand at higher income deciles, from +0.8% at the bottom to +1.5% at the top. Heterogeneity between workers occurs primarily within rather across deciles: the spread between the 10th and 90th percentiles is 2–4p.p. To facilitate the comparison of magnitudes of the various channels, Panel A(ii) normalizes the change in the bottom decile to zero. The most important channels explaining the heterogeneous labor demand change across deciles are the differences in exposure to net exports and intermediate inputs, which both favor richer workers. Income and substitution effects do not play a significant role.

Panel B of Figure 6 reports the distributional effects of the 10% trade shock in general equilibrium. As with labor demand, heterogeneity in the equivalent variation is much larger within income deciles than across (Panel B(i)). Within each decile, the 10-90 gap in welfare effects is over 2 percentage points, while variation across income deciles is much smaller, from 2.1% in the first decile to 1.8% at the tenth. As a consequence, only 0.3% of the cross-worker variance is explained by income decile dummies (using the equation (6) decomposition). Supplementary Figure S9 reports the share of workers who experience a negative welfare change after the shock. Despite positive average gains at all income levels, there are 4.4–8.5% of losers in each decile.[36]

It is notable that, in contrast to Panel A, the average gains in Panel B are slightly *higher* at the bottom of the income distribution. The change in slope when accounting for the $\tilde{\boldsymbol{G}}$ matrix is explained by the role of the service sector. In Appendix C.2 we show that when labor demand grows, less traded industries, such as services, experience a larger increase in wages. Since services also have relatively more lower-income workers, this larger wage response benefits the low-income group more.[37]

Next, Panel B(ii) of Figure 6 decomposes welfare changes in GE, relative to the first decile, into the earnings and expenditure channels. The panel shows that the

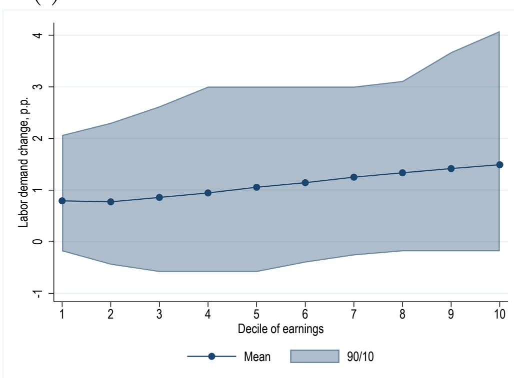
[36]The fraction of losers varies non-monotonically with income. While Panel A of Figure S9 reports the overall fraction of losers, Panel B shows that they are found especially within goods-producing industries, in which some industries suffer from import competition.

[37]Intuitively, the own-wage elasticity of labor demand is higher for more traded industries because the strongest substitutability in our model is between domestic and foreign varieties within an industry. When domestic wages grow, prices of domestic varieties increase, inducing shifts in demand. Both domestic and foreign buyers can substitute away to foreign varieties in manufacturing, but not so much in services. To the best of our knowledge, this channel has not been analyzed in prior work. In particular, it is distinct from the "manufacturing-services substitution channel" in Cravino and Sotelo (2019), which is subsumed in our analysis of substitution effects in Panel F of Figure 5.

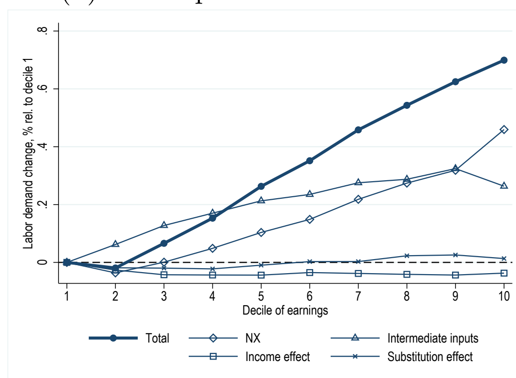
Figure 6: Worker-Level Welfare Effects of a 10% Fall in Trade Costs
by Income Decile

A: Partial equilibrium labor demand response

(i) Across and within income deciles

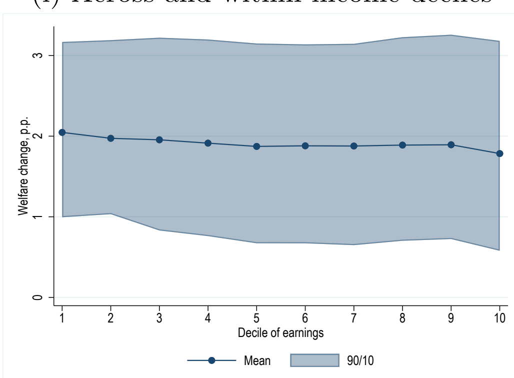


(ii) Decomposition into channels

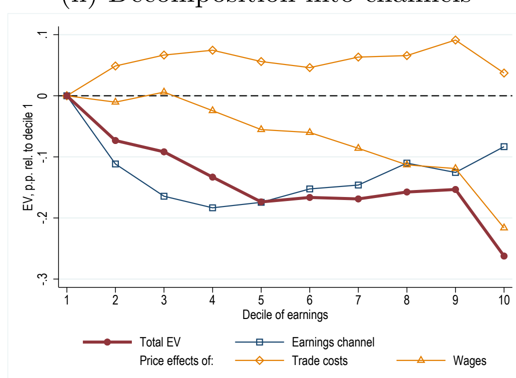


B: General equilibrium welfare response

(i) Across and within income deciles



(ii) Decomposition into channels



Notes: For the worker-level calibration of Section 5.3, this figure plots the labor demand (Panel A) and welfare (Panel B) responses following a uniform 10% fall in trade costs across and within deciles of worker initial earnings. Welfare changes are defined as the equivalent variation as a fraction of initial expenditures. For each decile, Panels A(i) and B(i) report the averages along with 10th and 90th percentiles. Panels A(ii) and B(ii) consider decile averages, with the bottom decile normalized to zero, and decompose them into different channels according to Proposition 2 and equation (2).

Table 3: Distributional Effects vs. Changes in Inequality (Worker-Level Calibration)

A: Unequal effects of the shock across workers

	SD (1)	p10 (2)	p50 (3)	p90 (4)
Welfare change, p.p.	1.44	0.73	2.30	3.16

B: Effects of the shock on inequality

	SD(log wage) (1)	p10 (2)	p50 (3)	p90 (4)	Gini index (5)
Initial income level	0.8230	10,700	32,500	90,000	0.4509
Counterfactual	0.8225	10,838	33,086	90,517	0.4507
Change	–0.0005	+1.29%	+1.80%	+0.57%	–0.0002

Notes: Panel A reports statistics of the distribution of welfare changes across workers after a uniform 10% fall in trade costs in the worker-level calibration of Section 5.3. Panel B shows how the same shocks affects the income distribution, by reporting statistics for two income distributions: the one observed in the data and the counterfactual one, in which the estimated welfare effects is added to each worker's initial wage. Both panels show the standard deviation and 10th, 50th, and 90th percentiles, while Panel B additionally reports Gini indices.

lower welfare gain for higher-income workers is explained primarily by the earnings channel. Compared with the first income decile, the fall in prices from lower trade costs, which affect both direct and indirect imports, benefits richer workers slightly more because the import share of their consumption baskets is slightly higher, exactly as in Figure 1. Prices also change because domestic wages increase in general equilibrium; the figure shows that this channel is biased against high-income workers.

Finally, Table 3 contrasts the unequal distribution of the welfare gains with the impact of the shock on inequality. Panel A shows that the shock has very heterogeneous effects across workers: while the median welfare gain is 2.30%, it is below 0.73% for 10% of workers and over four times larger, above 3.16% for another 10% of them. The standard deviation of the welfare changes is 1.44p.p. Despite this large heterogeneity in welfare gains, Panel B shows that the effect of the shock on inequality is very small. To measure this effect, we add the estimated welfare change to the initial (nominal) income of each worker and obtain changes in the distribution of "real wages," e.g. $\mathrm{SD}(\log X + \log \mathcal{W}) - \mathrm{SD}(\log X)$. The shock leaves the income distribution essentially unchanged: the Gini index fall by 0.0002 points, while the standard deviation of (real) log-wages falls by 0.0005. As shown in equation (7) the standard deviation of real wages can remain unchanged despite large distributional effects of the shocks, if the magnitude of welfare gains does not covary with the initial level of income. Thus, we find that the standard deviation of welfare effects is 26 times larger than the change in the standard deviation of the log-income distribution.

This analysis yields three lessons. First, the distributional effects are primarily concentrated within income deciles, rather than across. There is little impact of a fall in trade costs on overall inequality, but there are substantial distributional effects creating sizable changes in relative wages, as well as winners and losers at all income levels. This finding is not a mechanical feature of the model but results from the fact that the welfare effects of trade shocks are only weakly correlated with income. If specialization patterns had been sufficiently different across income deciles, we could have found an effect across deciles as large as the effect obtained within deciles.[38] Second, the average gains from trade liberalizations are positive for all income deciles. Third, the expenditure channel remains distributionally neutral even after accounting changes in domestic wages.

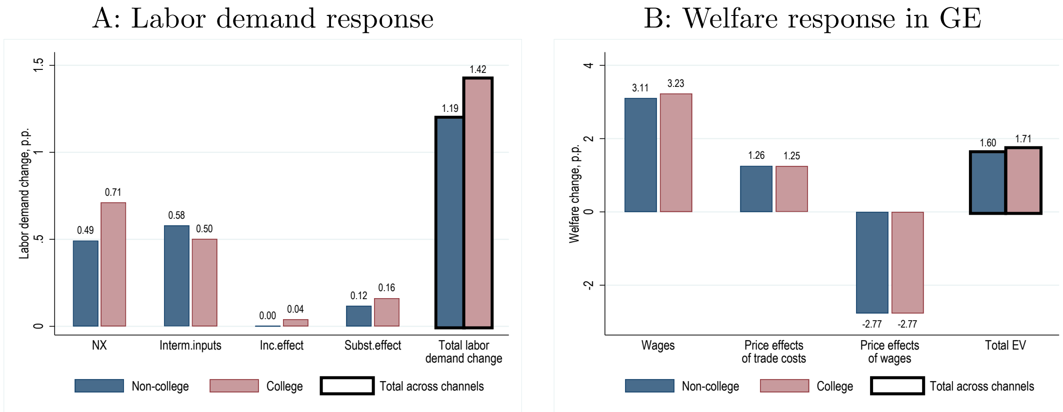
5.4 Distributional Effects across Education Groups

To verify that there is a robust pattern of weak distributional effects across groups of observably similar workers in general equilibrium, we now study a calibration with two groups — those with and without a college degree — assuming they are freely mobile across industries. Our focus is therefore on the college wage premium, which has played an important role in the evolution of U.S. income inequality (e.g. Autor et al. (2008) and Goldin and Katz (2007)). Figure 7 reports the effects of a 10% reduction in trade costs in this setting.

Using Proposition 2, Panel A reports shifts in labor demand and their drivers across education groups. We find that labor demand grows by more for college grad-

[38] This first lesson from our analysis echoes the empirical findings of Hummels et al. (2014) who estimate the effects of exports and offshoring on wages of different groups of workers in a reduced-form framework. The economic mechanisms they study are different, as our framework does not incorporate offshoring (although it can be introduced by modeling it as skill-biased import competition, as in our previous working paper (Borusyak and Jaravel 2018)). Yet, they find that the distributional effects of globalization arise primarily *within* groups of ex-ante similar workers because of their heterogeneous exposure (Table 6).

Figure 7: Welfare Effects of a 10% Fall in Trade Costs across Education Groups



Notes: For the calibration of Section 5.4, this figure plots the partial equilibrium change in labor demand (Panel A) and the welfare change in GE (Panel B) for workers with and without a college degree, following a uniform 10% reduction in trade costs. Welfare changes are defined as the equivalent variation as a fraction of initial expenditures. Each panel decomposes the effects into several channels according to Proposition 2 and equation (2).

uates, mainly because they are employed in industries with higher "net exports." Favorable income and substitution effects magnify the difference slightly, while exposure to imported inputs is lower for college graduates, which partially offsets the gap. In total, labor demand grows by 1.4% for the group of college graduates and 1.2% for the workers without a college degree in response to the shock.

Panel B reports welfare changes across education groups in general equilibrium. We find that both groups benefit from reduced trade costs and the college wage premium remains almost unchanged. The equivalent variation is 1.7% for college-educated workers, compared with 1.6% for those without a college degree; the small difference of 0.11p.p. arises from the earnings channel.

Taken together, the results of our two calibrations show that the distributional effects of trade arise when labor mobility is limited, and primarily within groups of ex-ante similar workers; cross-group differential effects are not found either with or without labor mobility. These results also illustrate how Proposition 2 can be used to assess the importance of different mechanisms and different labor market assumptions in governing the distributional effects of trade shocks.

5.5 Extensions

We now consider several extensions, allowing for other counterfactual shocks, within-industry heterogeneity, capital as a separate factor, and other choices of elasticities.

Non-uniform changes in trade costs. First, we consider reductions of trade costs with specific trading partners, as well as counterfactuals inspired by recent changes in trade policy and trade costs. Supplementary Figure S10 analyzes a 10% fall in iceberg costs for imports from China, NAFTA or 34 advanced economies separately, for the worker-level calibration. Figure S11 investigates the impact of the import tariffs introduced by the Trump administration in 2018 (on solar panels, washing machines, steel and aluminum products, and a large set of products from China), the observed change in U.S. import tariffs in 1992–2007, and the observed change in transportation and insurance costs in the same period.[39] Figure S12 repeats the same analyses across education groups. The results are similar to the baseline analyses: the expenditure channel is modest, and substantial distributional effects of trade are found only within income deciles in the absence of labor mobility.

Within-industry heterogeneity. To assess the potential importance of within-industry heterogeneity, in Supplementary Table S6 we use the plant-level microdata from the Census of Manufactures and the Management and Organizational Practices Survey (see Appendix S.2.8 for data construction). These data allow us to analyze, at a more granular level, one of the channels from Proposition 2: the difference in exposure to exports between skill groups, as measured by education groups or groups of non-production and production workers. We find that more skill-intensive plants within the same industry tend to export more (in line with Burstein and Vogel (2017)). However, this within component is small relative to differences arising across manufacturing industries, which we have analyzed previously.

Relative factor demand for capital and labor. Supplementary Figure S13 documents changes in factor demand for capital vs. labor after a fall in trade costs, quantifying all channels from Proposition 2: exposure to net exports, intermediate inputs, income, and substitution effects. We find that relative factor demand remains similar after a uniform fall in trade costs.

[39] Appendix S.2.7 describes the data sources and explains how to apply Proposition 2 to shocks which are not uniform across industries.

Robustness to choice of elasticities. Supplementary Figure S14 shows that the welfare effects of the uniform 10% in both our calibrations remain similar when we vary the trade elasticity $\xi - 1$, substitution elasticities in demand (ρ and ε) or the labor substitution elasticity σ_{macro} within the ranges used in the literature. Since exposure to trade is similar across worker groups, elasticities do not play a decisive role.

6 Conclusion

This paper has presented new evidence on the distributional effects of trade in the United States. Using new linked datasets, we found that import shares are flat across the income distribution, implying – contrary to a still widely held view – that the gains from lower trade costs via the expenditure channel are distributionally neutral. In addition, we accounted for changes in both prices and wages in a unified general equilibrium framework and found that the distributional effects of trade are mostly "horizontal" (within income groups) rather than "vertical" (across groups). Thus, our findings run against a popular narrative that "trade wars are class wars" (Klein and Pettis 2020).

The approach we took to investigate the distributional effects of trade in the United States could serve as a blueprint to investigate the expenditure and earnings channels of shocks in other contexts, including other major changes in trade policy (e.g., Brexit), but also changes in technology or immigration. Indeed, the effect of technology and migration shocks on price indices and wages across households groups can be studied using the unified exposure approach we applied to trade shocks. The framework could also be extended to analyze the impacts of shocks on regional inequality, provided that suitable data are available to measure exposure at the regional level. These extensions constitute promising avenues for research and policy design.

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Online Appendix to "The Distributional Effects of Trade: Theory and Evidence from the United States"

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A Proofs of Section 2.1 Results

Proof of Equation (2).

For a differentiable indirect utility function $\mathcal{V}$, equivalent variation EV_i for consumer i solves, by definition:

$$\mathcal{V}(p^0, X_i^0 + EV_i) - \mathcal{V}(p^0, X_i^0) = \mathcal{V}(p^0 + dp, X_i^0 + dX_i) - \mathcal{V}(p^0, X_i^0),$$

which for small shocks to prices and total expenditures implies

$$\frac{\partial \mathcal{V}}{\partial X} EV_i = \frac{\partial \mathcal{V}}{\partial X} dX_i + \frac{\partial \mathcal{V}}{\partial p} dp,$$
$$EV_i = dX_i - \left(- \frac{\partial \mathcal{V}/\partial p}{\partial \mathcal{V}/\partial X} \right) dp = dX_i - \sum_\omega q_\omega^i dp_\omega,$$

where q_ω^i is the initial consumption of ω, and the last equality holds by Roy's identity. Thus,

$$d \log \mathcal{W}_i \equiv \frac{EV_i}{X_i} = \frac{dX_i}{X_i} - \sum_\omega s_\omega^i \frac{dp_\omega}{p_\omega} = d \log X_i - \sum_\omega s_\omega^i d \log p_\omega.$$

Proof of Proposition 1.

Under Assumption 1, prices are equal to marginal costs. For variety ω produced in country $\gamma(\omega)$, the marginal cost (or unit cost) is denoted by m_ω, and the cost minimization problem implies

$$m_\omega = M_\omega \left(\left\{ m_\ell \tau_{\ell \gamma(\omega)} \right\}_{\ell \in \Omega}, w_{\gamma(\omega)} \right), \tag{8}$$

where M_ω is the cost function, Ω is the set of all varieties produced anywhere, $\tau_{\ell\gamma(\omega)}$ are the iceberg trade costs for delivering input ℓ (produced in country $\gamma(\ell)$) to country $\gamma(\omega)$, and $w_{\gamma(\omega)}$ is the vector of factor prices in country $\gamma(\omega)$. We assume system (8) has a unique solution around the initial equilibrium. Since factor prices do not change by Assumption 2, Shephard's lemma implies:

$$
\begin{aligned}
d\log m_\omega &= \sum_{\ell\in\Omega} \beta_\ell^\omega \left(d\log \tau_{\ell\gamma(\omega)} + d\log m_\ell\right) \\
&= \sum_{\ell\in\Omega} \beta_\ell^\omega d\log \tau_{\ell\gamma(\omega)} + \sum_{\ell\in\Omega} \beta_\ell^\omega \sum_{k\in\Omega} \beta_k^\ell d\log \tau_{k\gamma(\ell)} + \dots, \qquad (9)
\end{aligned}
$$

where β_ℓ^ω is the direct cost share of intermediate input ℓ in the production of ω.[40] Intuitively, the change in the unit production cost of ω depends on changes in the costs of all intermediate inputs through changes in trade costs, including higher-order terms along domestic and international supply chains.

Since we consider counterfactual shocks to trade costs between foreign suppliers c and and the Home country only (rather than between foreign suppliers), the only non-zero terms in (9) correspond to inputs directly imported from c to H. By Assumption 3, varieties ω produced abroad and imported into H use no inputs from Home. Therefore, the unit production costs for imported products remain unchanged, i.e. $d\log m_\omega = 0$ for all imported varieties. By perfect competition and complete pass-through, consumer prices in H for varieties imported from c change in proportion to changes in trade costs: $d\log p_\omega = d\log \tau$ for $\omega \in \Omega_c$, with $d\log p_\omega = 0$ for all other imported varieties.

For varieties that are domestically produced, the change in consumer price reflects changes in domestic production costs through intermediate inputs, i.e. $d\log p_\omega = d\log m_\omega$, and (9) simplifies to

$$
\begin{aligned}
d\log m_\omega &= \underbrace{\sum_{\ell\in\Omega_c} \beta_\ell^\omega d\log \tau}_{\text{direct impact on unit cost}} + \underbrace{\sum_{\ell\in\Omega_H} \beta_\ell^\omega d\log m_\ell}_{\text{indirect impact via domestic IO linkages}} \\
&= \left(\sum_{\ell\in\Omega_c} \beta_\ell^\omega + \sum_{\ell\in\Omega_H} \beta_\ell^\omega \sum_{k\in\Omega_c} \beta_k^\ell + \dots\right) d\log \tau \equiv \widetilde{IP}_{\omega c}^{\text{Int}} d\log \tau,
\end{aligned}
$$

Here the second line is a sum across all domestic supply chains fragments starting from a good imported from c and leading to the production of ω. Summation across them yields the overall share of inputs imported from c in ω's total production cost,

[40] The direct cost share is defined as $\beta_\ell^\omega = m_\ell \tau_{\ell\gamma(\omega)} q_\ell^\omega / m_\omega$, where q_ℓ^ω is the unit requirement of input ℓ in production of ω in equilibrium.

$\widetilde{IP}^{\text{Int}}_{\omega c}$, that satisfies the recursive definition of footnote 11 and measures the sensitivity of the output price to the change the iceberg costs.

Given the expressions above for price changes above, and since total expenditures do not change when earnings do not change,[41] Proposition 1 follows by (2).

Proof of Equation (3).

Define $\widetilde{IP}_{\omega c}$ as $\widetilde{IP}^{\text{Int}}_{\omega c}$ for $\omega \in \Omega_H$, 1 for $\omega \in \Omega_c$, and 0 otherwise. Then we have:

$$\begin{aligned} ImpSh^i_c - ImpSh^0_c &= \sum_{\omega} \left(s^i_\omega - s^0_\omega\right) \widetilde{IP}_{\omega c} \\ &= \sum_r \left(s^i_r ImpSh^i_{rc} - s^0_r ImpSh^0_{rc}\right) \\ &= \sum_r \left(s^i_r - s^0_r\right) ImpSh^0_{rc} + \sum_r s^i_r \left(ImpSh^i_{rc} - ImpSh^0_{rc}\right). \end{aligned}$$

B Parametric Frameworks

In this appendix, we provide details for the setting and results from Section 4: first for the AIDS demand system of Fajgelbaum and Khandelwal (2016, henceforth FK), and then for the nested NNHCES demand system we employ instead.

B.1 AIDS Demand System

Preferences. We first briefly review the AIDS demand system used by FK and their estimation procedure, based on bilateral trade data from the World Input-Output Database at the country-industry level. The demand system, with the "extended Cobb-Douglas" restrictions imposed by FK, is given by the following indirect utility function:

$$\mathcal{V}(w,p) = \frac{\log w - a(p)}{\exp\left(\sum_{j,c} \beta_{jc} \log p_{jc}\right)},$$

where j indexes $J = 35$ industries (including both goods and services and assuming that there are no intermediate goods), c indexes $C = 40$ countries, a constraint

[41] We maintain the proportionality of expenditures and earnings even in Section 5.1 where we allow for trade imbalances and thus the budget constraint violated at the aggregate country level.

$\sum_{j,c}\beta_{jc}=0$ is imposed, and

$$a(p)=\underline{\alpha}+\sum_{j,c}\alpha_{jc}\log p_{jc}+\frac{1}{2}\sum_{j}\gamma_j\left(\frac{1}{C}\left(\sum_{c}\log p_{jc}\right)^2-\sum_{c}\left(\log p_{jc}\right)^2\right).$$

By Roy's identity and as long as an interior solution exists, demand can be written in the share form as

$$s_{jc}\left(w,p\right)=\left(\alpha_{jc}-\beta_{jc}a(p)\right)+\beta_{jc}\log w-\gamma_j\left(\log p_{jc}-\frac{1}{C}\sum_{c'}\log p_{jc'}\right). \tag{10}$$

We return to the issue of corner solutions below.

Assuming all consumers in the same country n face the same prices p^n, the expenditure share on each variety is linear in log-income, $\frac{\partial s_{jc}(w,p^n)}{\partial \log w}=\beta_{jc}$. As a consequence, there exists an income level w_n such that country's aggregate expenditure share s^n_{jc} observed in the trade data equals $s_{jc}(w_n,p^n)$. When the income distribution within a country is not observed, this representative consumer income can be approximated, e.g. by calibrating a log-normal income distribution as in FK.[42] Predicting expenditure shares for consumers with income $w\neq w_n$ is straightforward given β_{jc}:

$$s_{jc}(w,p^n)=s^n_{jc}+\beta_{jc}\left(\log w-\log w_n\right). \tag{11}$$

The demand system thus extrapolates from the observed expenditure share for the representative agent, s^n_{jc}, to the rest of the income distribution via the estimated Engel curve.

Estimation. A key challenge when estimating the demand parameters with cross-country data is that prices are unobserved. FK address this challenge by assuming a simple structure of iceberg trade costs, whereby the price p^n_{jc} of variety (j,c) in country n is given by

$$\log p^n_{jc}=\log m_{jc}+\rho' d_{jcn}+\epsilon^n_{jc}. \tag{12}$$

Here m_{jc} is a unit production cost, ρ captures the relationship between trade costs and measures of proximity between the countries, d_{jcn}, such as the log of geographic

[42] There is a minor error in how this approximation is done by FK, which we fixed in our replication. Specifically, with $\log w\sim\mathcal{N}\left(\mu_n,\sigma_n^2\right)$, it is easy to verify that $\log w_n=\mu_n+\sigma_n^2$, while the code by FK instead used $\log w_n=\mu_n+\sigma_n$, meaning that the representative consumer was attributed to an incorrect percentile of the income distribution unless $\sigma_n=1$. However, for many countries including the U.S. the calibrated σ_n is not far from one.

distance or an indicator for common language, all interacted with industry indicators, and ϵ_{jc}^{n} is an error term. FK then plug in (12) into (10) evaluated at $w = w_n$ to obtain the non-homothetic gravity equation; see their Section IV.A for details of the estimation procedure.

Mechanical pro-poor expenditure channel within industries. We now show that, in the presence of home bias and income-inelastic tradable industries, the AIDS demand system mechanically generates pro-poor differences in import shares across the income distribution, which arise within industries.

First, note that in equation (11) the expenditure share of a variety is less sensitive to consumer income (in terms of elasticities) in countries that have a higher expenditure share on that variety. Log-differentiating (11) around $w = w_n$, we have

$$\frac{\partial \log s_{jc}\left(w_n, p^n\right)}{\partial \log w} = \frac{\beta_{jc}}{s_{jc}^{n}}. \tag{13}$$

Using this result, consider the predictions of AIDS regarding import shares within goods-producing industries across the income distribution. Denoting $\beta_{j,-n} = \sum_{c \neq n} \beta_{jc}$, $\beta_j = \sum_c \beta_{jc}$, and similarly $s_{j,-n}^{n} = \sum_{c \neq n} s_{jc}^{n}$ and $s_j^n = \sum_c s_{jc}^{n}$, (11) implies that the import share within tradable industry j is

$$IP_j^n(w, p^n) \equiv \frac{s_{j,-n}^{n}\left(w, p^n\right)}{s_j^n(w, p^n)} = \frac{s_{j,-n}^{n} + \beta_{j,-n}\left(\log w - \log w_n\right)}{s_j^n + \beta_j\left(\log w - \log w_n\right)}. \tag{14}$$

In the data, all but one goods-producing industries are income-inelastic, i.e. have $\beta_j < 0$. For income-inelastic industries, differentiating (14) yields the following condition for the import share in industry j to decline with income w: $\frac{\partial IP_j^n(w,p^n)}{\partial \log w} < 0$ if and only if

$$\frac{s_{j,-n}^{n}}{s_j^n} < \frac{\beta_{j,-n}}{\beta_j}. \tag{15}$$

Whether this condition holds in the data generally depends on the Engel curve parameters. With the estimates of FK, this condition holds for 599 out of the 600 pairs of (j, n) within goods-producing income-inelastic industries. This is due to home bias: the import share in industry j on the left-hand side tends to be far below one; the median import share among these (j, n) pairs is 39%. In contrast, the right-hand side of (15) tends to be close to one, since $\beta_{j,-n}$ and β_j are sums of 39 and 40 country parameters that differ only by one term (corresponding to the domestic Engel curve parameter, β_{jn}). Intuitively, (15) almost always holds because the income elasticity of foreign varieties is magnified due to home bias, per equation (13). In the single exception case, the estimated domestic Engel curve parameter, β_{jn}, is sufficiently large, overturning this effect.

We have thus shown that with AIDS the fraction of import spending within goods-producing industries is predicted to fall with income, because of the combination of home bias and the fact that these industries are almost all income-inelastic. However, applying the same derivations to services may seem to imply that an offsetting pattern should arise for income-elastic services, i.e. low-income consumers should have lower import shares within services. In fact, corner solutions prevent this offsetting effect from operating in practice.

As mentioned, equation (10) only applies to interior solutions. However, corner solutions are common in the estimated demand system of FK: for example, a U.S. consumer at the 25th percentile of the income distribution is predicted to have zero shares on 1,015 out of 1,365 foreign varieties, particularly in services (658 out of 741 varieties).[43] This happens because, according to (11), the expenditure share on income-elastic varieties, characterized by $\beta_{jc} > 0$, can turn negative for incomes just slightly below w_n, specifically when $w < w_n \exp\left(-s^n_{jc}/\beta_{jc}\right)$. This issue is most relevant for foreign services which have particularly low observed trade shares s^n_{jc} and tend to be income-elastic. Appendix A of FK describes an iterative procedure which removes these negative shares, yielding the appropriate corner solution. This procedure sets the negative shares to zero (e.g., for an imported service variety) and scales down the shares of other varieties in the same industry (e.g., for the domestic service variety). Therefore, for lower-income consumers the fraction of foreign services is not significantly lower than for the representative consumer, as it rapidly hits a

[43] These zero shares are due to the extrapolation in equation (10): there are *no* zero shares in the observed data s^n_{jc} for $n =$ U.S. Corner solutions are key for understanding two important results obtained by FK. First, without corner solutions it would be impossible to have import shares fall with income in all countries. Indeed, assuming (10) holds and aggregating it across all domestic varieties ($c = n$) yields that the total domestic expenditure share grows with income if and only if domestic varieties are more income elastic than the world average: $\frac{\partial \sum_j s_{jn}}{\partial \log w} = \sum_j \beta_{jn}$, where the world average of the right-hand side terms, $\frac{1}{C}\sum_c \sum_j \beta_{jn}$, is zero. Yet, the import shares in the estimated FK model do fall with income in all countries, e.g. comparing the 25th and 75th percentiles (see Panel A of our Figure 4 for the U.S. as an example). Second, for the same reason it would be impossible for import shares to have a region of growth at the top of the distribution, producing an overall U-shape, while this is again the case in the estimates of FK for all countries (see again Panel A of Figure 4 for the U.S.).

corner and stays at zero. In contrast, the share of foreign goods in the consumption basket (and within the total spending on goods) falls with income according to (11).[44]

B.2 Nested Non-Homothetic CES

We now consider a nested version of the non-homothetic CES utility function of Comin et al. (2021), which we define recursively by

$$\begin{aligned} \mathcal{U} &= \left(\sum_j Q_j^{(\varepsilon-1)/\varepsilon} \right)^{\varepsilon/(\varepsilon-1)}, \\ Q_j &= \left(\sum_c \left(a_{jc} \mathcal{U}^{\varphi_{jc}(\xi_j-1)} \right)^{1/\xi_j} Q_{jc}^{(\xi_j-1)/\xi_j} \right)^{\xi_j/(\xi_j-1)}. \end{aligned} \tag{16}$$

Here the first line is a CES aggregate of consumption across industries (outer nest), with elasticity ε, and the second line defines sectoral consumption Q_j as an aggregate of quantities Q_{jc} across country-specific varieties with elasticity $\xi_j > 1$ and taste shifters a_{jc}. Primitive parameters $\varphi_{jc} < 1$ determine how non-homothetic tastes $a_{jc}\mathcal{U}^{\varphi_{jc}(\xi_j-1)}$ vary with consumer utility; we will show that high φ_{jc} translates into high income elasticity of the variety.[45]

It is straightforward to derive utility-dependent price indices:

$$\begin{aligned} p_j^* &= \left(\sum_c a_{jc} \mathcal{U}^{\varphi_{jc}(\xi_j-1)} p_{jc}^{1-\xi_j} \right)^{1/(1-\xi_j)}, \\ \pi^* &= \left(\sum_j p_j^{*\,1-\varepsilon} \right)^{1/(1-\varepsilon)}, \end{aligned} \tag{17}$$

[44] The same mechanism explains the slight U-shape in import shares found by FK. For income levels sufficiently above w_n the shares of income-inelastic imported goods hit the zero bound. Those high-income consumers are therefore predicted to buy a lot of foreign services, and this cannot be compensated by a lower share of foreign goods (which is already 0%), such that the import share begins to rise. Such U-shape is an inherent feature of AIDS under home bias: it would arise whenever there are *any* differences in income elasticities across industries; it is more severe for incomes below the representative agent's because home bias is particularly strong for income-elastic services.

[45] Our way of writing the utility function differs slightly from that of Comin et al. (2021) to better resemble traditional nested CES when $\varphi_{jc} \equiv 0$. A single-tier version of (16) is equivalent to equation (1) in Comin et al. (2021) with $1 - \varphi_{jc}$ as relevant income elasticity parameters. As in Comin et al. (2021), a parameter restriction $\varphi_{jc} < 1$ is required for integrability.

such that the agent's utility always satisfies at the optimal consumption bundle:

$$\mathcal{U} = w/\pi^*. \tag{18}$$

The Hicksian expenditure shares are then given by

$$s_{jc} \equiv \underbrace{\frac{a_{jc}\mathcal{U}^{\varphi_{jc}(\xi_j-1)}p_{jc}^{1-\xi_j}}{p_j^{*1-\xi_j}}}_{s_{c|j}} \cdot \underbrace{\frac{p_j^{*1-\varepsilon}}{\pi^{*1-\varepsilon}}}_{s_j}. \tag{19}$$

Income and substitution patterns with NNHCES. We first show how expenditure shares vary with income and prices. Define $\bar{\varphi}_j = \sum_c s_{c|j}\varphi_{jc}$ and $\bar{\varphi} = \sum_j s_j\bar{\varphi}_j$. Log-differentiating (17) we have:

$$d\log p_j^* = \sum_c s_{c|j}\left(d\log p_{jc} - \varphi_{jc} d\log\mathcal{U}\right) = d\log p_j - \bar{\varphi}_j d\log\mathcal{U}, \tag{20a}$$

$$d\log\pi^* = \sum_j s_j d\log p_j^* = d\log\pi - \bar{\varphi} d\log\mathcal{U}, \tag{20b}$$

where $\mathrm{d}\log\mathcal{U}$ is the log-change in cardinal utility, while $d\log p_j = \sum_c s_{c|j} d\log p_{jc}$ and $d\log\pi = \sum_j s_j d\log p_j$ are the industry-level and overall Laspeyres price indices for the consumer, respectively. Together with (18), (20b) implies

$$d\log\mathcal{U} = d\log w - d\log\pi^* = \frac{d\log w - d\log\pi}{1-\bar{\varphi}}. \tag{21}$$

This equation relates changes in the cardinal utility to observable objects only: the money metric of the welfare gain $d\log\mathcal{W}$ (change in the total expenditure minus the Laspeyres price index) and spending shares at the original equilibrium (which enter $\bar{\varphi}$).

We can now express changes in demand in terms of observables: log-differentiating (19) and plugging in (20) and (21) yields

$$\begin{aligned} d\log s_{jc} &= \varphi_{jc}\left(\xi_j-1\right)d\log\mathcal{U} + \left(1-\xi_j\right)\left(d\log p_{jc} - d\log p_j^*\right) + \left(1-\varepsilon\right)\left(d\log p_j^* - d\log\pi^*\right) \\ &= \left(1-\xi_j\right)\left(d\log p_{jc} - d\log p_j\right) + \left(1-\varepsilon\right)\left(d\log p_j - d\log\pi\right) \\ &\quad + \left(\psi_{jc}-1\right)\left(d\log w - d\log\pi\right), \end{aligned} \tag{22}$$

where the income elasticity of variety jc is given by

$$\psi_{jc} = 1 + \frac{\left(\xi_j-1\right)\left(\varphi_{jc}-\bar{\varphi}_j\right) + \left(\varepsilon-1\right)\left(\bar{\varphi}_j-\bar{\varphi}\right)}{1-\bar{\varphi}}. \tag{23}$$

According to (22), the change in the expenditure share on variety jc has three components. The first two are identical to conventional nested CES, capturing the substitution effects across varieties within the industry and across industries, respectively. The third term is the income effect, shaped by the income elasticity ψ_{jc}. When welfare increases ($d \log w - d \log \pi > 0$), so does the spending share on income-elastic products (those with $\psi_{jc} > 1$).

Equation (23) implies that NNHCES, in contrast with AIDS, does not produce the mechanical relationship between the income elasticity and the spending shares on that variety. Indeed, it is immediate from (23) that if two varieties in the same industry j from countries c and c' have the same $\varphi_{jc} = \varphi_{jc'}$, then $\psi_{jc} = \psi_{jc'}$ for every consumer in the world.[46] More generally, among two varieties in the same industry, the one with higher φ_{jc} is always more income-elastic for every consumer: $\psi_{jc} - \psi_{jc'} = (\varphi_{jc} - \varphi_{jc'}) \frac{\xi_j - 1}{1 - \bar{\varphi}}$, with $\frac{\xi_j - 1}{1 - \bar{\varphi}}$ always positive. While this demand system is flexible and can capture that certain varieties are high- or low-income elastic (with correspondingly high or low φ_{jc}), it does not hard-wire differences between foreign and domestic varieties.

Baseline estimation. We now estimate the key φ_{jc} parameters by adapting the non-homothetic CES estimation strategy proposed by Comin et al. (2021, Appendix A.2.2) to accommodate nests and the cross-country setting of FK. We assume that the observed equilibrium is generated by identical NNHCES preferences, and each country n is populated by representative agents with known income w_n.[47] We further assume that price differences across countries follow equation (12). We focus on estimating φ_{jc}, assuming that $\xi_j \equiv \xi$ and ε are known (we use $\xi = 3.5$ and $\varepsilon = 2$ as in Section 5.2).

We also impose a normalization. Like in the single-tier version of Comin et al. (2021), preferences are over-parameterized, in that rescaling all $1 - \varphi_{jc}$ by a positive constant only changes the cardinal value of utility but does not affect preferences or Marshallian demand. We therefore assume, without loss of generality, that the

[46] Like in every non-homothetic demand system, income elasticities still vary across income groups, via $\bar{\varphi}_j$ and $\bar{\varphi}$ in (23).

[47] Because non-homothetic CES preferences do not admit a positive representative consumer (Mas-Colell et al. 1995, p.116), this should be viewed as an approximation. However, the same issue arises for AIDS when corner solutions exist for some consumers in the country, as is the case for FK. For comparability with FK we use the same representative consumer (see footnote 42). Estimation of either demand system without invoking representative consumers would be a useful avenue for future work.

average of $1-\varphi_{jc}$ across all varieties, weighted by their output shares λ_{jc} in the world output at the observed equilibrium, equals one. For any variable z_{jc} we denote $\check{z}=\sum_{jc}\lambda_{jc}z_{jc}$, with conventions that $\log\check{z}=\sum_{jc}\lambda_{jc}\log\check{z}_{jc}$ (with the log taken before averaging) and $\check{z}^{n}=\sum_{jc}\lambda_{jc}z_{jc}^{n}$.

We now derive the estimating equation. First, using (19) and (18), we define augmented expenditure shares in each country n which eliminate the complications related to the two-tier structure of our demand system:

$$S_{jc}^{n}\equiv s_{c|j}^{n}\left(s_{j}^{n}\right)^{(1-\xi)/(1-\varepsilon)}=a_{jc}\mathcal{U}_{n}^{(\varphi_{jc}-1)(\xi-1)}\left(\frac{p_{jc}^{n}}{w_{n}}\right)^{1-\xi}$$

or, in the log form,

$$\log S_{jc}^{n}=\log a_{jc}+(\xi-1)\left(\log w_{n}-\log p_{jc}^{n}\right)+(\varphi_{jc}-1)(\xi-1)\log\mathcal{U}_{n}. \tag{24}$$

Averaging (24) across j,c with weights λ_{jc} and using the imposed parameter normalization $\check{\varphi}=0$, we solve for the unknown $\log\mathcal{U}_{n}$ in each country:

$$\log\check{S}^{n}-\log\check{a}-(\xi-1)\left(\log w_{n}-\log\check{p}^{n}\right)=-(\xi-1)\log\mathcal{U}_{n}. \tag{25}$$

We can now substitute for utility in (24) to obtain a function of expenditure shares and prices only. Plugging (25) and rearranging terms yields

$$\begin{aligned}\log S_{jc}^{n}-\log\check{S}^{n}=&\left(\log a_{jc}-\log\check{a}\right)-(\xi-1)\left(\log p_{jc}^{n}-\log\check{p}^{n}\right)\\&-\varphi_{jc}\left(\log\check{S}^{n}-\log\check{a}-(\xi-1)\left(\log w_{n}-\log\check{p}^{n}\right)\right).\end{aligned}$$

Finally, plugging in the structure of iceberg trade costs from (12), we obtain[48]

$$\begin{aligned}\log S_{jc}^{n}-\log\check{S}^{n}=&FE_{jc}-(\xi-1)\rho'\left(d_{jcn}-\check{d}_{n}\right)\\&+\varphi_{jc}\left[(\xi-1)\log w_{n}-\log\check{S}^{n}-(\xi-1)\rho'\check{d}_{n}\right]+\tilde{\epsilon}_{jc}^{n},\end{aligned} \tag{26}$$

where FE_{jc} is the variety fixed effect invariant to the importer,[49] and the error is given by

$$\tilde{\epsilon}_{jc}^{n}=-(\xi-1)\rho'\left(\epsilon_{jcn}-\check{\epsilon}_{n}\right)-\varphi_{jc}(\xi-1)\rho'\check{\epsilon}_{n}.$$

We estimate equation (26) by nonlinear least squares where unknown parameters

[48]We note that because of (12) the model does not permit zero trade shares, which are found in the trade data, particularly for some service industries. We therefore winsorize the shares from below at the first % percentile of non-zero shares (1.04×10^{-10}), which affects 9.4% observations, almost all of which correspond to foreign varieties in service industries.

[49]Specifically, $FE_{jc}=\log a_{jc}+(\varphi_{jc}-1)\log\check{a}-(\xi-1)\log m_{jc}-(\xi-1)(\varphi_{jc}-1)\sum_{jc}\lambda_{jc}\log m_{jc}$.

are φ_{jc} and FE_{jc} for each of the 1,400 varieties, as well as 140 gravity parameters ρ. Specifically, we use the gravity variables d_{jcn} from FK (log of geographic distance and indicators for common border and common language) as well as the indicator for $c = n$ to capture border effects; these four variables are interacted with 35 industry indicators to allow for industry-specific elasticities, as in FK.[50]

Identification of the key parameters φ_{jc} in equation (26) is very intuitive: a variety is more income elastic if richer countries buy relatively more of it, conditionally on prices captured by the gravity terms. This logic applies because the terms in square brackets recover the utility of the representative agent by adjusting her nominal income for price differences, and φ_{jc} is estimated, given ρ, by a cross-country regression of relative shares (adjusted for the nesting structure) on this imputed utility measure.

Constrained estimation. As explained in the main text, baseline estimates of NNHCES predict that goods overall are too income-inelastic, compared with what we see in the CEX data. We therefore re-estimate the parameters φ_{jc} keeping within-industry differences in income elasticities as in the baseline estimation but adjusting across-industry differences. We match the income elasticity of tradable goods for the U.S. representative consumer to the value of 0.864 obtained from our CEX-IO data of Section 2.2 (see Appendix S.2.5).

Concretely, equation (23) shows how within- and across-industry differences in φ_{jc} parameters respectively translate into within- and across-industry differences in income elasticities. We therefore take the baseline estimates $\varphi_{jc}^{\text{baseline}}$ and ρ^{baseline} and look for across-industry shifts $\Delta\varphi_j$ such that $\varphi_{jc} = \varphi_{jc}^{\text{baseline}} + \Delta\varphi_j$ best fits (26) while imposing

$$\frac{\sum_{j\in\text{goods}} \sum_c s_{jc}^{\text{US}} \psi_{jc}^{\text{US}}}{\sum_{j\in\text{goods}} \sum_c s_{jc}^{\text{US}}} = 0.864 \tag{27}$$

Given $\varphi_{jc}^{\text{baseline}}$ and ρ^{baseline}, estimation of (23) becomes linear.[51]

Inferring expenditure shares across the income distribution. We finally explain how we use the estimated demand system to impute the expenditure shares for

[50]To ease computation we note that, conditionally on ρ, (26) is linear. We therefore perform nonlinear search over ρ only. Moreover, to satisfy the the integrability constraint $\varphi_{jc} < 1$ and avoid numerical instability, we impose the constraints $\varphi_{jc} \leq 0.9$; these constraints are binding for only 5.5% of varieties, many of which in the pseudo-industry "Private Households."

[51]Goods-producing industries are those coded 1–16 in the data of FK. We continue to require that $\sum_{j,c} \lambda_{jc}\varphi_{jc} = 0$ and $\varphi_{jc} \leq 0.9$.

consumers at various levels of consumer income, as in Panels B and C of Figure 4. This procedure is based on exact hat algebra and does not involve any approximation. We will use hats here to denote exact log-differences between the representative consumer with income w_n (the initial point) and a consumer with income level w (the end point, marked by primes). For example, $\hat{w} = \log \frac{w}{w_n}$ and $\hat{s}_{jc} = \log \frac{s_{jc}(w,p^n)}{s^n_{jc}}$.

Log-differencing (19) between w_n and w and noting that price indices p^*_j and π^* are income-dependent implies:

$$\hat{s}_{jc} = \varphi_{jc} \left(\xi_j - 1\right) \hat{\mathcal{U}} + \left(\xi_j - 1\right) \hat{p}^*_j + \left(1 - \varepsilon\right) \left(\hat{p}^*_j - \hat{\pi}^*\right). \tag{28}$$

To solve for $\hat{\mathcal{U}}$, $\hat{\pi}^*$, and $\hat{p}^*_j$, we use (17) and (18) to write

$$\left(1 - \xi_j\right) \hat{p}^*_j = \log \frac{\sum_c a_{jc} \left(\mathcal{U}'\right)^{\varphi_{jc}(\xi_j - 1)} p_{jc}^{1-\xi_j}}{\sum_c a_{jc} \mathcal{U}^{\varphi_{jc}(\xi_j - 1)} p_{jc}^{1-\xi_j}} = \log \sum_c s_{c|j} \exp \left(\varphi_{jc} \left(\xi_j - 1\right) \hat{\mathcal{U}}\right) \tag{29a}$$

and similarly

$$\left(1 - \varepsilon\right) \hat{\pi}^* = \log \sum_j s_j \exp \left(\left(1 - \varepsilon\right) \hat{p}^*_j\right), \tag{29b}$$

$$\hat{\mathcal{U}} = \hat{w} - \hat{\pi}^*. \tag{29c}$$

Combining the three lines in (29) we arrive at an equation in $\hat{\mathcal{U}}$ only:

$$\hat{\mathcal{U}} = \hat{w} - \frac{1}{1 - \varepsilon} \log \sum_j s_j \exp \left(\frac{1 - \varepsilon}{1 - \xi_j} \log \sum_c s_{c|j} \exp \left(\varphi_{jc} \left(\xi_j - 1\right) \hat{\mathcal{U}}\right) \right),$$

which is solved numerically for each $\hat{w}$ of interest. Substituting $\hat{\mathcal{U}}$ back to (29a), (29b), and (28), we retrieve the extrapolated shares as $s_{jc}\left(w, p^n\right) = s^n_{jc} \exp\left(\hat{s}_{jc}\right)$ for each variety.

C Details and Proofs of Section 5.1 Results

Appendix C.1 proves Proposition 2 and characterizes the welfare changes for each worker after a uniform trade shock in GE. Appendix C.2 then considers special cases: with NNHCES demand system and with the structure of the labor market as in each of our two calibrations. Finally, Appendix C.3 proves the first-order approximation for the effects of trade shocks on inequality, equation (7).

C.1 Proof of Proposition 2

We consider changes in the $I \times 1$ vector of wages w and the $J \times 1$ vector of value-added by industry (measured in monetary terms) VA. We allow not only trade costs but also the $I \times 1$ labor supply vector L (measured in efficiency units) to change. This additional generality will be useful to define the macro elasticity of factor demand.

We first derive two equations, respectively characterizing labor and product market equilibria in log-changes:

$$d \log w = \boldsymbol{E} \cdot d \log VA + \boldsymbol{V} \cdot d \log w - d \log L, \tag{30}$$

$$d \log VA = \eta \cdot (-d \log \tau) + \boldsymbol{G} \cdot d \log w + \boldsymbol{D} \cdot d \log VA, \tag{31}$$

where $\boldsymbol{E}$, $\boldsymbol{V}$, $\boldsymbol{G}$, and $\boldsymbol{D}$ are matrices that we characterize and discuss later (see equations (35), (36), (44), and (45), respectively). We prove Proposition 2 using these equations. We then apply equation (2) to characterize the welfare change for each worker.

Labor market equilibrium and proof of (30). Let $v_{i|j}$ be the share of value added from industry j that accrues to labor type i (with $\sum_i v_{i|j} = 1$) and, conversely, $e_{j|i}$ be the share of total labor income of type i that stems from industry j (with $\sum_j e_{j|i} = 1$). We start from an accounting identity, that the total wage payments of type i labor equal the sum of wage payments across industries, which can be expressed as:

$$w_i L_i = \sum_j v_{i|j} \cdot VA_j, \tag{32}$$

with summation across $j \in \mathcal{J}_i$. Log-differentiating it yields

$$d \log w_i + d \log L_i = \sum_j e_{j|i} \left(d \log v_{i|j} + d \log VA_j \right). \tag{33}$$

We now argue that changes in the composition of payroll across types in a given industry, $d \log v_{i|j}$, depend fully on the wage changes without direct effects of trade costs or total labor supply. This follows from our assumption on the production function, in which all labor inputs enter via an aggregator F^{VA}. Thus, the optimal composition of labor per unit of value added solves

$$W_j \equiv \min_{L_1^j \ldots L_I^j} \sum_i w_i L_i^j \quad \text{s.t. } F_j^{VA}(L_1^j, \ldots, L_I^j) \geq 1. \tag{34}$$

This problem yields within-industry payroll shares $v_{i|j}(w)$, which are homogeneous functions of degree 0 that depend on wages only and capture patterns of labor substitution within the industry. This problem also yields the value-added cost index W_j which we will use later. Thus,

$$d\log v_{i|j} = \sum_{i'=1}^{I} \frac{\partial \log v_{i|j}}{\partial \log w_{i'}} d\log w_{i'}.$$

Together with (33), this implies (30), with matrix

$$\boldsymbol{E} = \left(e_{j|i}\right)_{i,j} \tag{35}$$

collecting worker exposures to different industries and matrix

$$\boldsymbol{V} = \left(\sum_j e_{j|i} \frac{\partial \log v_{i|j}}{\partial \log w_{i'}}\right)_{i,i'} \tag{36}$$

collecting cross-industry averages of labor substitution elasticities between types i and i'. Intuitively, the wage of type i workers increases if the industries in which these workers are employed expand, and falls if either supply of these workers or wages of substitutable workers grow.

Product market equilibrium and proof of (31). To derive equation (31) for value-added changes in each industry, we first solve for the price changes after the shock, similar to Proposition 1 but allowing for wage changes. We then use price and income elasticities, as well as the structure of foreign demand and domestic intermediate demand, to translate the price and consumer income changes into VA changes.

Changes in prices. We first explain how Assumption 4 implies that relative price indices and relative product demand do not change in foreign countries in response to the counterfactual shock. Consider some foreign variety ω belonging to industry j. Since exports to Home are assumed to be a small fraction of ω's worldwide sales, shocks to trade costs with H have negligible effects on the total demand for ω. Likewise, shocks to wages in H have a negligible impact on total demand for ω. Moreover, since imports from Home are a small fraction of absorption abroad, shocks to trade costs and to wages in H have negligible impacts on industry-j consumer price indices in all foreign countries. Thus, the demand for variety ω from consumers outside H remains unchanged after the shocks. These observations have direct implications for factor prices, since factor demand arises from the relative demand for goods: absent changes in relative demand, relative foreign factor prices stay constant.[52]

Turning to the domestic economy, Proposition 1 extends naturally to characterize changes in the industry consumer prices P_{jH} and the prices of domestic varieties, p_{jH}. Log-differentiating the consumer price index (i.e. the CES aggregator of consumer prices across selling countries for a given industry), we have by Roy's identity:

$$d\log P_{jH} = IP_{jc} d\log\tau + (1 - IP_j)\, d\log p_{jH}. \tag{37}$$

By Shephard's lemma and using perfect competition,

$$d\log p_{jH} = (1-\beta_j)\, d\log W_j + \sum_{\ell=1}^{J} \beta_\ell^j d\log P_{jH}. \tag{38}$$

Denote the domestic input requirement (i.e., input-output) matrix by $\boldsymbol{B} = \left(\beta_\ell^j\right)$, and by $\tilde{\boldsymbol{B}} = \left(\mathbb{I}_J - \mathrm{diag}\,(1 - IP_j)\,\boldsymbol{B}'\right)^{-1}$ its Leontief inverse matrix, such that $\tilde{\boldsymbol{B}}y$ is a weighted sum of variable y in the reference industry j and in all upstream industries in the domestic supply chain of j. Solving the system of (37)–(38) yields

$$d\log p_{jH} = \widetilde{IP}^{\mathrm{Int}}_{jc} d\log\tau + \left(1 - \widetilde{IP}^{\mathrm{Int}}_{j}\right) d\log\tilde{W}_j \qquad \text{and} \tag{39a}$$

$$d\log P_{jH} = \widetilde{IP}_{jc} d\log\tau + \left(1 - \widetilde{IP}_{j}\right) d\log\tilde{W}_j, \tag{39b}$$

where $\left\{\widetilde{IP}_{jc}\right\}_{j=1}^{J} = \tilde{\boldsymbol{B}} \cdot \{IP_{jc}\}_{j=1}^{J}$ collects the IO-adjusted shares of imports from c in industry absorption, $\left\{\widetilde{IP}^{\mathrm{Int}}_{j}\right\} = \boldsymbol{B} \cdot \left\{\widetilde{IP}_{j}\right\}$ collects the shares of imported inputs in the costs of domestic varieties, and $d\log\tilde{W}_j$ is the average change in the value added cost in the domestic part of the supply chain resulting in j, defined by

$$\left\{\left(1 - \widetilde{IP}_j\right) d\log\tilde{W}_j\right\} = \tilde{\boldsymbol{B}} \cdot \left\{\left(1 - \widetilde{IP}_j\right)(1-\beta_j)\, d\log W_j\right\}. \tag{40}$$

Domestic price changes in (38) imply consumer price changes for domestic varieties in foreign countries: after a bilateral liberalization, prices change by $d\log p_{jH}$ in

[52] More formally, one could consider the effects of a trade shock in a sequence of economies with the share of Home in imports and exports abroad converging to zero, while domestic trade shares do not change along the sequence to match our data. In the limit, the effects of the trade shock on foreign prices become negligible, even though the responses of the demand for Home's varieties and relative goods and factor prices at Home remain non-vanishing.

countries other than c and by $d\log p_{jH} + d\log\tau$ in c. Equation (37), in turn, yields the Laspeyres price index for a domestic consumer with income x, as

$$d\log P_x = \sum_j s_j^x d\log P_{jH} = ImpSh_c^x d\log\tau + \sum_j s_j^x \left(1-\widetilde{IP}_j\right) d\log\tilde{W}_j. \tag{41}$$

Changes in industry sizes. To characterize the change in industry VA, as required by (30), we first observe that it equals the change in the value of industry output Y_{jH}, i.e. $d\log VA_j = d\log Y_{jH}$. This follows since production functions are Cobb-Douglas in value added and inputs. To characterize changes in domestic output, we start from the product market clearing condition: domestic output can be sold to domestic final and intermediate consumers, or as exports. That is, $Y_{jH} = Y_{jH}^{\text{Final}} + Y_{jH}^{\text{Int}} + Y_{jH}^{\text{Export}}$, where $Y_{jH}^{\text{Int}} = \sum_k Y_{jH}^k$ measures total intermediate sales as a sum across domestic downstream industries k. The change in total sales is thus determined by the shares of different modes of sales at the initial equilibrium and by the changes in each component after the shock.

We use the IO table to measure the composition of different modes of sales. A challenge arises because the IO table does not fully report modes of sales. Specifically, the IO table reports the share of exports *in output* and the share of final consumers and each downstream industry k *in absorption*. Modes of sales can be computed using the proportionality condition (see footnote 26). Specifically, we introduce the intermediate absorption coefficients $\delta_j^k = Y_j^k/\text{Absorption}_j$ which measure the share of industry j's absorption that is used as intermediate inputs to downstream industry k. While β_k^j characterize industry j's suppliers, δ_j^k characterize its buyers. By proportionality, shares δ_j^k can be applied to the domestic sales of *domestic* varieties specifically, i.e. $Y_{jH}^k/\left(Y_{jH}^{\text{Final}} + X_{jH}^{\text{Int}}\right) = \delta_j^k$. Therefore, the share of domestic output that goes to k equals $Y_{jH}^k/Y_{jH} = DomSalesSh_j \cdot \delta_j^k$. Similarly, the share of domestic output that is sold to domestic final consumers is $DomSalesSh_j \cdot (1-\delta_j) \equiv DFS_j$, where $\delta_j = \sum_k \delta_j^k$ measures the share of intermediate sales in absorption. As a result,

$$d\log VA_j = ExSh_j \cdot d\log Y_{jH}^{\text{Export}} + DFS_j \cdot d\log Y_{jH}^{\text{Final}} + \sum_{k=1}^{J} DomSalesSh_j \delta_j^k \cdot d\log Y_{jH}^k. \tag{42}$$

We now turn to the changes in each component of sales in (42). First, consider exports to some country $c' \neq H$. Since the consumer price for the domestic variety in j changes in country c' by $d\log p_{jH} + \mathbf{1}[c' \in c]\, d\log\tau$, purchases by final and intermediate buyers in c' change by

$$d\log Y_{jH}^{\text{Export},c'} = d\log Y_j^{c'} + (1-\xi_j)\left(d\log p_{jH} + \mathbf{1}[c' \in c]\, d\log\tau - d\log P_{jc'}\right),$$

where $Y_j^{c'}$ is the total spending on all varieties of j by all buyers in c' and $P_{jc'}$ is the industry price index in that country. By Assumption 4, $d\log P_{jc'} = 0$ and $d\log Y_j^{c'} = 0$. Thus, exports to an individual country change by $d\log Y_{jH}^{\text{Export},c'} = (1-\xi_j)\left(d\log p_{jH} + \mathbf{1}[c' \in c]\, d\log\tau\right)$. Aggregating across foreign countries, we have

$$ExSh_j \cdot d\log Y_{jH}^{\text{Export}} = (1-\xi_j)\left(ExSh_j d\log p_{jH} + ExSh_{jc} d\log\tau\right).$$

Second, domestic final sales in (42) are the total of purchases by various consumer groups defined by type i and initial income level x, Y_{jH}^{ix}, and thus

$$d\log Y_{jH}^{\text{Final}} = \sum_{x,i} \mu_{x,i|j} d\log Y_{jH}^{ix},$$

where $\mu_{x,i|j}$ captures the composition of final buyers of industry j by income and labor market type.[53] By the assumption of CES preferences within industries, $d\log Y_{jH}^{ix} = d\log Y_j^{ix} + (1-\xi_j)\left(d\log p_{jH} - d\log P_{jH}\right)$, where Y_j^{ix} measures total spending by the consumer group on industry j varieties, domestic or foreign. By definition of income and price elasticities,

$$\begin{aligned} d\log Y_j^{ix} &= \psi_{jx} d\log w_i + \sum_{k=1}^{J} \varepsilon_{xjk} d\log P_{kH} \\ &= d\log w_i + (\psi_{jx}-1)\left(d\log w_i - d\log P_x\right) + \sum_{k=1}^{J} \varepsilon_{xjk}\left(d\log P_{kH} - d\log P_x\right). \end{aligned} \tag{43}$$

Here in the first line we equated expenditure and wage changes using the assumption that each consumer spends a constant multiple of their income. The second line used $\psi_{jx} + \sum_k \varepsilon_{xjk} = 1$, which follows because increasing income and prices proportionately does not change expenditure shares.

Finally, for intermediate sales in (42) we use the Cobb-Douglas assumption again.

[53] Because labor market data (e.g. industries) are not available for the consumers in the CEX, we do not observe $\mu_{x,i|j}$ directly. However, with identical non-homothetic preferences the industry does not matter for consumption baskets conditionally on income. Thus, we measure $\mu_{x,i|j}$ as the product of the share of income decile x in the CEX expenditures on industry j, $\mu_{x|j}$, and the share of type-i workers in the total payroll of workers in income decile x in the ACS, $v_{i|x}$.

The share of spending by industry k on *all* varieties of j is fixed, so the change in expenditures equals the change in k's value added: $d\log Y_j^k = d\log Y_{kH} = d\log VA_k$. But substitution between domestic and foreign varieties implies that domestic sales of j to k change by

$$d\log Y_{jH}^k = d\log VA_k + (1-\xi_j)\left(d\log p_{jH} - d\log P_{jH}\right).$$

Equation (31) now follows by plugging price changes derived above into the expressions for the changes in exports, domestic final sales, and domestic intermediate sales, plugging those in turn into (42), and rearranging terms. Specifically, all terms that enter with $-d\log\tau$ are collected in the η vector, yielding (5). The terms with $d\log VA_k$, arising from intermediate demand only, define the $\boldsymbol{D}$ matrix:

$$\boldsymbol{D} = \left(DomSalesSh_j \cdot \delta_j^k\right)_{j,k}. \tag{44}$$

Pre-multiplication by its Leontief inverse $\tilde{\boldsymbol{D}} = \left(\mathbb{I}_J - \boldsymbol{D}\right)^{-1}$ is interpreted as the IO adjustment that accounts for the propagation of shocks from downstream industries up through changes in domestic intermediate demand. For example, the elements of $\tilde{\boldsymbol{D}} \cdot ExSh$ are the shares of domestic output that is exported either directly or indirectly (by selling to domestic downstream industries that export).

Finally, collecting the terms related to wage changes defines the $\boldsymbol{G}$ matrix, as follows:

$$\begin{aligned}
(\boldsymbol{G}w)_j \equiv{} & (1-\xi_j)\left(ExSh_j + DomSalesSh_j IP_j\right)\left(1-\widetilde{IP}_j^{\text{Int}}\right) d\log\tilde{W}_j \\
& + DFS_j \sum_{x,i} \mu_{x,i|j}\left[d\log w_i + (\psi_{jx}-1)\left(d\log w_i - \sum_{\ell=1}^{J} s_\ell^x \left(1-\widetilde{IP}_\ell\right) d\log\tilde{W}_\ell\right)\right. \\
& \left. + \sum_{k=1}^{J} \varepsilon_{xjk}\left(\left(1-\widetilde{IP}_k\right) d\log\tilde{W}_k - \sum_{\ell=1}^{J} s_\ell^x\left(1-\widetilde{IP}_\ell\right) d\log\tilde{W}_\ell\right)\right],
\end{aligned} \tag{45}$$

with $d\log\tilde{W}_k$ linearly related to $d\log w$ via (40). The first line of (45) captures the loss of competitiveness of domestic varieties (relative to foreign varieties in the same industry) in both domestic and foreign markets when domestic wages grow. The second line captures the change in domestic final demand when consumer incomes change, as well as income effects from changing both consumer income and inflation. The third line captures the substitution effects driven by domestic wage changes.

Proof of Proposition 2. Letting $\tilde{\boldsymbol{V}} = (\mathbb{I}_I - \boldsymbol{V})^{-1}$, (31) implies

$$d \log VA = \tilde{\boldsymbol{D}} \left(-\eta \cdot d \log \tau + \boldsymbol{G} \cdot d \log w\right).$$

and, from (30),

$$\begin{aligned} d \log w &= \tilde{\boldsymbol{V}} \left(\boldsymbol{E} \cdot d \log VA - d \log L\right) \\ &= \tilde{\boldsymbol{V}} \left(-\boldsymbol{E}\tilde{\boldsymbol{D}}\eta \cdot d \log \tau + \boldsymbol{E}\tilde{\boldsymbol{D}}\boldsymbol{G} \cdot d \log w - d \log L\right) \\ &= \tilde{\boldsymbol{G}} \left(\boldsymbol{E}\tilde{\boldsymbol{D}}\eta \cdot (-d \log \tau) - d \log L\right). \end{aligned} \tag{46}$$

Here

$$\tilde{\boldsymbol{G}} = \left(\mathbb{I}_I - \tilde{\boldsymbol{V}}\boldsymbol{E}\tilde{\boldsymbol{D}}\boldsymbol{G}\right)^{-1} \tilde{\boldsymbol{V}} \tag{47}$$

captures the GE response of factor prices to an exogenous decline in factor supply and therefore can be interpreted as the (negative of the) inverse labor demand elasticity matrix. With $d \log L = 0$, equation (46) reduces to (4), establishing Proposition 2. We note that the $\tilde{\boldsymbol{G}}$ matrix generalizes the macro elasticity of factor substitution that Oberfield and Raval (2020) derived for a closed economy with homothetic preferences and only two factors.

Welfare effects in general equilibrium. Given wage changes characterized by Proposition 2, we can obtain welfare changes for workers of type i with initial income x. We have:

$$\begin{aligned} d \log \mathcal{W}_{ix} = {} & (d \log w_i - d \log \bar{w}) - ImpSh_c^x d \log \tau \\ & + ImpSh^x d \log \bar{w} - \sum_j s_j^x \left(1 - \widetilde{IP}_j\right) \left(d \log \tilde{W}_j - d \log \bar{w}\right), \end{aligned} \tag{48}$$

where $ImpSh^x$ is the total share of imports from all foreign countries in the consumption baskets. The first term here is the earnings channel, capturing the gap between wage growth of type i relative to the economy overall, with the latter defined as $d \log \bar{w} = \sum_i v_i d \log w_i$ where v_i denotes the initial payroll share of type i in the economy. The second term is the partial equilibrium effect on prices from Proposition 1. The third term is a terms-of-trade adjustment: if domestic wages grow on average, all imports become relatively cheaper. The final term captures the idea that, if some group of consumers tends to buy goods from industries where wages grow relatively more after the shock (directly or in their supply chains), this group will benefit less. For instance, if college graduates buy goods produced with skilled labor, then increases in the skill premium generate an offsetting effect on inequality via the expenditure channel; we label this mechanism a "segregation effect."[54]

Proof of equation (48). We have:

$$
\begin{aligned}
d\log \mathcal{W}_{ix} &= d\log w_i - d\log P_x \\
&= d\log w_i - ImpSh_c^x d\log\tau - \sum_j s_j^x \left(1-\widetilde{IP}_j\right) d\log \tilde{W}_j \\
&= d\log w_i - ImpSh_c^x d\log\tau - \left(1-ImpSh^x\right) d\log \bar{w} \\
&\quad - \sum_j s_j^x \left(1-\widetilde{IP}_j\right)\left(d\log \tilde{W}_j - d\log \bar{w}\right) \\
&= \left(d\log w_i - d\log \bar{w}\right) - ImpSh_c^x d\log\tau + ImpSh^x d\log \bar{w} \\
&\quad - \sum_j s_j^x \left(1-\widetilde{IP}_j\right)\left(d\log \tilde{W}_j - d\log \bar{w}\right).
\end{aligned}
$$

Here the first line used the Roy identity, the second equation used (41), the third line used the definition of $ImpSh^x = \sum_j s_j^x \widetilde{IP}_j$, and the last line rearranged the terms.

C.2 Special Cases

We now consider special cases of Proposition 2. We first characterize the substitution effects in η (see equation (5)) under the nested non-homothetic CES demand system our calibrations employ. We then discuss how the general formulas simplify in our two calibrations. In particular, for the worker-level calibration we explain why wages in less traded sectors are more sensitive to labor demand shocks. For the calibration across education groups, we show how the local elasticities of labor substitution in all industries can be summarized with a single "macro" elasticity.

Substitution effects with NNHCES. As described in Section 5.2, we discipline substitution effects by NNHCES preferences, analogous to those of Appendix B.2 but using a different tier structure. With the assumption on CES aggregation across varieties in each industry, we require the income elasticities parameters φ_j to be the same for those varieties (see footnote 26). Relative to Appendix B.2, we allow for

[54] For the analyses of this effect, see Clemens et al. (2018) and Wilmers (2017), as well as our early draft (Borusyak and Jaravel 2018). In Figures 6B(ii) and 7B we combine the last two terms into the "price effects of wages" total.

additional flexibility by adding goods and services as a separate upper tier, indexed by r:

$$\mathcal{U} = \left(\sum_{r=\text{Goods, Services}} Q_r^{(\rho-1)/\rho} \right)^{\rho/(\rho-1)},$$
$$Q_r = \left(\sum_{j \in r} \left(\mathcal{U}^{\varphi_j(\varepsilon_r - 1)} \right)^{1/\varepsilon_r} Q_j^{(\varepsilon_r-1)/\varepsilon_r} \right)^{\varepsilon_r/(\varepsilon_r-1)}, \tag{49}$$

where Q_j is a CES aggregator across country varieties: $Q_j = \left(\sum_c a_{jc}^{1/\xi_j} Q_{jc}^{(\xi_j-1)/\xi_j} \right)^{\xi_j/(\xi_j-1)}$.

We now show that, for industry j that belongs to sector r, substitution effects in (5) satisfy:

$$\sum_{k=1}^{J} \varepsilon_{xjk} \left(\widetilde{IP}_{kc} - ImpSh_c^x \right) = (1-\varepsilon_r) \left(\widetilde{IP}_{jc} - ImpSh_{rc}^x \right)$$
$$+ (1-\rho) \left(ImpSh_{rc}^x - ImpSh_c^x \right), \tag{50}$$

where $ImpSh_{rc}^x = \sum_{k \in r} s_{k|r}^x \widetilde{IP}_{kc}$, and similarly for the substitution effects in the last line of (45):

$$\sum_{k=1}^{J} \varepsilon_{xjk} \left(\left(1 - \widetilde{IP}_k\right) d\log \tilde{W}_k - \sum_{\ell=1}^{J} s_\ell^x \left(1 - \widetilde{IP}_\ell\right) d\log \tilde{W}_\ell \right) =$$
$$(1-\varepsilon_r) \left(\left(1 - \widetilde{IP}_j\right) d\log \tilde{W}_j - \sum_{k \in r} s_{k|r}^x \left(1 - \widetilde{IP}_k\right) d\log \tilde{W}_k \right)$$
$$+ (1-\rho) \left(\sum_{k \in r} s_{k|r}^x \left(1 - \widetilde{IP}_k\right) d\log \tilde{W}_k - \sum_{k=1}^{J} s_k^x \left(1 - \widetilde{IP}_k\right) d\log \tilde{W}_k \right) \tag{51}$$

Proof of (50)–(51). Analogously to (22), after a set of income and price changes, changes in expenditures of consumer i with income x on the aggregate good of industry j within sector r are given by

$$d\log Y_j^{ix} = d\log w_i + (\psi_{xj} - 1) \left(d\log w_i - \sum_{k=1}^{J} s_k^i d\log P_{kH} \right)$$
$$+ (1-\varepsilon_r) \left(d\log P_{jH} - \sum_{k \in r} s_{k|r}^i d\log P_{kH} \right) + (1-\rho) \left(\sum_{k \in r} s_{k|r}^i d\log P_{kH} - \sum_{k=1}^{J} s_k^i d\log P_{kH} \right). \tag{52}$$

We use this expression instead of the more general (43) and follow the remaining part of the proof of Proposition 2, plugging in prices from (39) and isolating the terms with $d\log\tau$ and $d\log\tilde{W}_k$. Then the substitution effects from the second line of (52) yield (50)–(51).

Worker-level calibration. We now consider how Proposition 2 applies to our worker-level calibration, which assumes no mobility of workers across industries.

In this setting, a labor type directly maps to an industry and $I = J$. Absent labor substitution, $\boldsymbol{V} = 0_{I\times I}$, and each labor type is exposed just to its own industry, $\boldsymbol{E} = \mathbb{I}_I$. By equation (30), wages are proportional to industry value added, $d\log w = d\log VA - d\log L$.

We now show that in industries with lower trade shares (i.e., export shares and import penetration rates), wages are more responsive to shifts in labor demand, compared to more traded industries. We prove this result in a restricted model, in which only the export and import competition effects arise, while intermediate inputs, income, and substitution channels are shut down. We find in our calibration of Section 5.3 that this result holds qualitatively even when all channels are operative.

Formally, suppose $\tilde{\boldsymbol{D}} = \mathbb{I}_J$, $\psi_{xj} \equiv 1$, and $\varepsilon_{xjk} \equiv 0$ and consider a set of shifts to labor demand $d\log L_j^D$ (or, equivalently, a similar reduction in labor supply). Then we prove that, for $d\log w = \tilde{\boldsymbol{G}} \cdot d\log L^D$,

$$d\log w_j = \frac{d\log L_j^D}{1+(\xi_j-1)\,T_j} + \frac{DomSalesSh_j}{\zeta_2\left(1+(\xi_j-1)\,T_j\right)} \cdot \left(\sum_{k=1}^{J} \frac{e_k d\log L_k^D}{1+(\xi_k-1)\,T_k}\right), \tag{53}$$

where $T_j = ExSh_j + IP_j \cdot DomSalesSh_j$, $\zeta_2 = 1 - \sum_j \frac{e_j DomSalesSh_j}{1+(\xi_j-1)T_j} \in (0,1)$, and e_j is the payroll share of industry j in the economy.

The first term in (53) shows that wages in more traded industries are less responsive to shifts in labor demand in their own industry, via the T_j term which increases in both the export share and the import penetration rate. The second term shows that they are also less sensitive to the economy average shift in labor demand, via both higher T_j and lower $DomSalesSh_j$.

Proof of equation (53). Under the above conditions, $DFS_j = DomSalesSh_j$. In the absence of non-homotheticities, $\sum_x \mu_{xi|j} = e_i$ for any j. Thus, equation (45) simplifies to

$$(\boldsymbol{G} \cdot d \log w)_j = (1 - \xi_j) T_j d \log w_j + DomSalesSh_j \cdot \sum_i e_i d \log w_i.$$

In matrix form,

$$\boldsymbol{G} = -\operatorname{diag}\left[(\xi_j - 1) T_j\right] + DomSalesSh \cdot e'.$$

By the Sherman-Morrison formula in linear algebra, its Leontief inverse equals

$$\tilde{\boldsymbol{G}} = \operatorname{diag}\left[1 + (\xi_j - 1) T_j\right]^{-1} + \frac{\operatorname{diag}\left[1 + (\xi_j - 1) T_j\right]^{-1} DomSalesSh \cdot e' \operatorname{diag}\left[1 + (\xi_j - 1) T_j\right]^{-1}}{1 - e' \operatorname{diag}\left[1 + (\xi_j - 1) T_j\right]^{-1} DomSalesSh}.$$

Expanding these terms, $\tilde{\boldsymbol{G}} \cdot d \log L^D$ satisfies (53).

Calibration across education groups. We next consider the setting with full labor mobility across industries and two labor types (e.g. education groups), which we denote H and L (high and low skilled). We show that labor substitution elasticities σ_j of all industries enter the $\boldsymbol{V}$ matrix (and therefore $\tilde{\boldsymbol{G}}$) only through a scalar parameter σ_{macro}, which we refer to as the macro elasticity of labor substitution. Specifically,

$$\boldsymbol{V} = (\sigma_{\text{macro}} - 1) \begin{pmatrix} -v_L & v_L \\ v_H & -v_H \end{pmatrix}, \tag{54}$$

where[55]

$$\sigma_{\text{macro}} - 1 = \sum_j e_j \frac{v_{H|j} v_{L|j}}{v_H v_L} (\sigma_j - 1). \tag{55}$$

.

We then use this result to show that the skill group that is initially specialized in industries that will grow faster after the shock will experience a higher wage growth:

$$d \log \frac{w_H}{w_L} = \frac{1}{\sigma_{\text{macro}}} \left(\sum_j v_{H|j} d \log VA_j - \sum_j v_{L|j} d \log VA_j \right). \tag{56}$$

Proof of (54)–(56). By definition of the labor substitution elasticity in j,

$$d \log \frac{v_{H|j}}{v_{L|j}} = (1 - \sigma_j) d \log \frac{w_H}{w_L}.$$

[55] We note that $\sigma_{\text{macro}} - 1$ is generally not a weighted average of $\sigma_j - 1$: the sum of weights, $\sum_j e_j \frac{v_{H|j} v_{L|j}}{v_H v_L}$, is smaller than one unless all industries have the same skill composition.

Since $v_{L|j} = 1 - v_{H|j}$ and using $d\log\frac{z}{1-z} = \frac{1}{1-z}d\log z$, we obtain:

$$d\log v_{H|j} = v_{L|j}\left(1-\sigma_j\right)d\log\frac{w_H}{w_L}. \tag{57}$$

Thus,

$$\boldsymbol{V}_{HH} = \sum_j e_{j|H}v_{L|j}\left(1-\sigma_j\right) = v_L\sum_j e_j\frac{v_{H|j}}{v_H}\frac{v_{L|j}}{v_L}\left(1-\sigma_j\right) = -v_L\left(\sigma_{\text{macro}}-1\right),$$

where the first equality follows by definition of and (57), the second one rewrites $e_{j|H} = \frac{e_j v_{H|j}}{v_H}$, and the last uses the definition of σ_{macro}. The other elements of $\boldsymbol{V}$ are obtained analogously, yielding (54). Plugging in (54) into (30) for $d\log w_H$ and $d\log w_L$ and taking the difference, one obtains (56).

C.3 Proof of Equation (7)

We consider a sequence of $d\log\mathcal{W} = W\,dt$ for a fixed random variable W and $dt\to 0$. Then:

$$\begin{aligned}
\text{SD}\left(\log X + W\,dt\right) &= \sqrt{\text{Var}\left[\log X\right] + 2\text{Cov}\left[\log X, W\right]dt + \text{Var}\left[W\right]dt^2} \\
&= \text{SD}\left(\log X\right)\cdot\sqrt{1 + 2\frac{\text{Cov}\left[\log X, W\right]}{\text{Var}\left[\log X\right]}dt + o(dt)} \\
&= \text{SD}\left(\log X\right)\left(1 + \frac{\text{Cov}\left[\log X, W\right]}{\text{Var}\left[\log X\right]}\cdot dt\right) + o(dt) \\
&= \text{SD}\left(\log X\right) + \text{Corr}\left[\log X, W\right]\cdot\text{SD}\left(W\right)dt + o(dt) \\
&= \text{SD}\left(\log X\right) + \text{Corr}\left[\log X, d\log\mathcal{W}\right]\cdot\text{SD}\left(d\log\mathcal{W}\right) + o(dt).
\end{aligned}$$

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Supplementary Material (Not For Publication) for "The Distributional Effects of Trade: Theory and Evidence from the United States"

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S Supplementary Materials

S.1 Extensions to Proposition 1

We now discuss how Proposition 1 can be extended to several important deviations from Assumptions 1–3.

GVCs. Two adjustments to Proposition 1 are required when the Home economy is involved in global value chains. First, some imported products are subject to iceberg trade costs multiple times, and the resulting price increases accumulate. Equation (9) shows how import shares need to be measured in that case: every imported intermediate input should be counted as many times as it crosses the border from c into H. Second, with GVCs, bilateral shocks to iceberg costs have additional price effects, as imported products may contain exported domestic products; again, equation (9) accommodates that case.

We note that our analysis, both in the baseline case and with GVCs, considers shocks to trade costs. However, it can easily be applied to studying productivity shocks in foreign countries. If, say, labor productivity increases in c, the relevant measure of the import share will be based on the fraction of value added in the costs of the final output that originated from c, regardless of the route it took to arrive in H.

Markups. Suppose firms are monopolists in the markets for each variety they sell but price takers in the markets for factors and intermediate inputs they buy, and that the set of available varieties does not change after the trade shock. If firms charge constant markups μ_ω, which are not affected by the trade shocks (but could differ across firms, as with monopolistic competition in multi-sectoral models), then Proposition 1 continues to hold.[56]

In contrast, Proposition 1 has to be adjusted if markups are not constant and respond endogenously to the counterfactual shocks. For standard demand systems with endogenous markups, the pass-through of marginal cost shocks into prices is incomplete (Arkolakis and Morlacco 2017). This could affect the expenditure channel if products purchased by different consumer groups systematically differ in their pass-through rates or in the length of supply chains, as incomplete pass-through at multiple stages of domestic production generates more attenuation. Another implication of endogenous markups for the expenditure channel is that, following a trade liberalization, firms might change their markups even absent a marginal cost change, because demand for each variety shifts. In particular, domestic prices could change through reduced markups due to increased foreign competition.

Endogenous Variety. While in our benchmark model the set of products in the consumption basket is assumed exogenous, Proposition 1 continues to hold in several classes of models where product variety changes in response to a trade liberalization. First, suppose some foreign varieties are not purchased by a consumer at the initial equilibrium because their prices are above reservation prices, but these varieties start to be consumed (with small shares) when prices fall after the trade liberalization. This could occur, for instance, in models with an Armington product space but non-CES

[56] From the measurement perspective, however, this case is more complex than perfect competition because the cost shares β_ω^ℓ no longer equal the revenue shares of the same inputs (see Tintelnot et al. 2020).

demand that features finite reservation prices. In this setting, the implied welfare effect of the new products is second order. Indeed, the envelope theorem underlying Proposition 1 continues to apply when expenditure shares on some products are null, as long as prices change continuously.

Second, a similar logic applies to Eaton and Kortum (2002) type models, with or without the Frechet distribution of productivity. Although in this model some imported products enter the domestic market with non-negligible quantities, they replace domestic varieties which are only marginally more expensive. Thus, by grouping perfectly substitutable varieties across countries, one can view consumer prices and expenditure shares as continuous in trade costs. The envelope theorem then continues to apply, even though prices and shares jump at the producing country-variety level, and this extensive margin response does not yield first-order welfare effects.

Finally, even if entry of foreign varieties generates first-order welfare gains, as in Melitz (2003) and Chaney (2008), it may be accompanied by exit of varieties produced domestically or in third countries. These effects exactly offset each other in some cases, as we show next.

Increasing Returns and Selection Effects. In this final extension, we show how Proposition 1 extends to a setting with increasing returns to scale and endogenous variety stemming from selection into exporting. We study the Generalized Melitz-Pareto model of Kucheryavyy et al. (2020), which enriches the standard Melitz-Pareto model of Chaney (2008) and Melitz (2003) by decoupling the scale and trade elasticities. This model is isomorphic to the Armington model with external scale economies and a generalized Krugman model (Kucheryavyy et al. 2020). As in Proposition 1, we consider partial equilibrium changes. We focus on selection and scale effects but abstract from changes in the numbers of potential entrants or in market size. This is without loss in single-sector settings; with multiple sectors, home market effects need to be accounted for but their welfare consequences were shown to be small (Costinot and Rodríguez-Clare 2015).

We focus on a particular industry, suppressing the j index. We assume that there is a continuum of varieties with (homothetic) nested CES preferences, in which the inner nest aggregates within each country with elasticity ς and the outer nest aggregates across countries with elasticity $\epsilon \leq \varsigma$, with $\epsilon = \varsigma$ corresponding to the standard Melitz model. In country c, an exogenous number N_c of potential entrants

ω draw productivity $z(\omega)$ from the Pareto distribution with the shape parameter $\kappa > \varsigma - 1$ and scale parameter $z_{\min,c}$ and choose which markets to sell in and how much to produce using labor as the single factor. For a firm born in c, the marginal cost of selling in H is $m_c \tau_{cH}/z(\omega)$, where m_c is the unit cost of production. Besides the iceberg cost τ_{cH}, exporting involves a fixed cost F_{cH} (expressed in monetary terms; in partial equilibrium, it is irrelevant whether this fixed cost is paid in the exporting or importing county's labor).

We now show that the industry consumer price index in the Home country, P_H, following a set of changes $d \log \tau_{cH}$ in iceberg trade costs from various countries c to H satisfies[57]

$$d \log P_H = \sum_c IP_c d \log \tau_{cH}, \tag{S1}$$

where IP_c is the expenditure share in H on goods imported from c within the industry. Aggregating price index changes across industries and focusing on a change in the costs of importing from a single country or group of countries, one obtains Proposition 1.

Proof of Equation (S1). With nested CES demand, the optimal gross markup is $\frac{\varsigma}{\varsigma-1}$. The consumer price index is given by:

$$P_H^{1-\epsilon} = \sum_c P_{Hc}^{1-\epsilon}, \tag{S2}$$

where the price aggregate of all varieties imported from c, P_{Hc}, is given by

$$\begin{aligned} P_{Hc}^{1-\varsigma} &= N_c \int_{z_{cH}}^{\infty} \left(\frac{\varsigma}{\varsigma - 1}\right)^{1-\varsigma} m_c^{1-\varsigma} \tau_{cH}^{1-\varsigma} z^{\varsigma-1} \cdot \frac{\kappa z^{-\kappa-1}}{z_{\min,c}^{-\kappa}} dz \\ &= \left(\frac{\varsigma}{\varsigma - 1}\right)^{1-\varsigma} \frac{\kappa z_{c,\min}^{\kappa}}{\kappa - (\varsigma - 1)} \cdot N_c m_c^{1-\varsigma} \tau_{cH}^{1-\varsigma} z_{cH}^{-\kappa+(\varsigma-1)}, \end{aligned} \tag{S3}$$

with z_{cH} denoting the productivity cutoff for exporting from c to H (or choosing to sell domestically in the case of $c = H$).

Log-differentiation of P_{Hc}, holding m_c and N_c fixed but allowing z_{cH} to respond, yields

$$d \log P_{Hc} = d \log \tau_{cH} + \frac{\kappa - (\varsigma - 1)}{\varsigma - 1} d \log z_{cH}.$$

Intuitively, when trade costs decrease, consumer prices at home fall at the intensive

[57] Summation here includes $c = H$, although $d \log \tau_{HH} = 0$ for shocks to international trade.

margin, with complete pass-through, and there is a correction for the number of exported varieties through love of variety.

Log-differentiating (S2) further yields the change in the aggregate domestic price index:

$$d\log P_H = \sum_c IP_c d\log P_{Hc} = \sum_c IP_c \left(d\log \tau_{cH} + \frac{\kappa - (\varsigma - 1)}{\varsigma - 1} d\log z_{cH} \right). \tag{S4}$$

To solve for changes in exporting cutoffs across countries, we consider the indifference condition for the decision to sell in H:

$$F_{cH} = Y_H \left(\frac{P_{Hc}}{P_H} \right)^{1-\epsilon} \left(\frac{\frac{\varsigma}{\varsigma-1} m_c \tau_{cH}/z_{cH}}{P_{Hc}} \right)^{1-\varsigma}.$$

With marginal costs m_c, fixed costs F_{cH}, and total market size Y_H held fixed, log-differentiating the indifference condition implies

$$\begin{aligned} 0 &= (1-\epsilon)\left(d\log P_{Hc} - d\log P_H\right) + (1-\varsigma)\left(d\log \tau_{cH} - d\log z_{cH} - d\log P_{Hc}\right) \\ &= (1-\epsilon)\left(d\log \tau_{cH} + \frac{\kappa - (\varsigma - 1)}{\varsigma - 1} d\log z_{cH} - d\log P_H \right) + \kappa d\log z_{cH}, \end{aligned}$$

and therefore

$$d\log z_{cH} = \zeta_1 \left(d\log \tau_{cH} - d\log P_H\right), \qquad \text{for } \zeta_1 = \left(1 + \frac{\kappa}{\epsilon - 1} - \frac{\kappa}{\varsigma - 1}\right)^{-1} > 0. \tag{S5}$$

Intuitively, less productive firms find it profitable to sell in H when trade costs fall, but the opposite happens when the domestic market becomes more competitive as measured by a lower consumer price index. Plugging (S5) into (S4) yields

$$\begin{aligned} d\log P_H &= \sum_c IP_c \left(d\log \tau_{cH} - \zeta_1 \frac{\kappa - (\varsigma - 1)}{\varsigma - 1} \left(d\log \tau_{cH} - d\log P_H\right) \right) \\ &= \left(1 + \zeta_1 \frac{\kappa - (\varsigma - 1)}{\varsigma - 1}\right) \sum_c IP_c d\log \tau_{cH} - \zeta_1 \frac{\kappa - (\varsigma - 1)}{\varsigma - 1} d\log P_H \\ &= \sum_c IP_c d\log \tau_{cH}. \end{aligned}$$

Thus, the response of the domestic price index is governed by import shares in the same way as without selection forces. This happens because two effects offset each other exactly. Lower trade costs induce entry of new varieties from countries where trade costs are falling. At the same time, higher competition pushes less productive firms from all countries out of the H market.

S.2 Data Replication Appendix

S.2.1 CEX-IO Data

Overview. To measure import shares by consumer group at the industry level, we merge consumption data from the Consumer Expenditure Survey (CEX) to the import shares measured using the U.S. Input-Output table. We focus on the year 2007, the most recent year for which the detailed IO table is available, although we check robustness to other years with more aggregated data.

The CEX is a survey by the U.S. Bureau of Labor Statistics that measures detailed expenditures on all goods and services for a representative panel of households. We use the Integrated survey of the CEX, which combines the complete coverage of the Interview survey with the high resolution of the Diary survey on a subset of the most frequently purchased items. These data include 668 detailed spending categories, while recording household characteristics, such as income and education. We pool data from 2006–2008 to increase sample size.

The IO table from the Bureau of Economic Analysis (BEA), in turn, allows us to measure direct and indirect import shares by industry, with 389 industries in total. BEA data are the most detailed available accounts of the entire U.S. economy. For each industry we compute import penetration as the fraction of imports in absorption (defined as output plus imports minus exports). There are two advantages of using the BEA data to measure import penetration: trade in services is accounted for and trade flows are measured from the same data as domestic output, which improves consistency. Then we build the input requirement matrix, which measures the composition of suppliers for each buying industry. We use it to construct the share of indirect imports (imports of intermediate inputs) in domestic production. Combining direct and indirect imports, we obtain the total import share in absorption of each industry.

We pay special attention to the "distribution margins," which refer to the costs of retailing, wholesaling, and transportation and by definition have a low import share. For example, when consumers buy apparel, much of their spending is effectively devoted to distribution margins. The IO table reports that imported final products constitute 84% of total absorption in the apparel industry; when accounting for domestic distribution costs, the import share shrinks to only 36%. We combine "producer-value" and "purchaser-value" IO tables to implement this adjustment.

We use additional tabulations from the U.S. Census Bureau to compute import shares for specific trading partners: China, NAFTA countries (Mexico and Canada), and 34 developed economies (OECD members as of 2017, excluding NAFTA, plus Taiwan and Singapore). Specifically, we compute the shares of these countries in the total 2007 U.S. imports in each industry. We then distribute the overall import penetration reported in the IO table across trade partners using these shares,[58] and combine direct and indirect imports from a given trade partner using the input requirement matrix.

Finally, we match CEX spending categories to 170 final industries in the IO table by building a manual concordance.[59] We use personal final consumption from the IO table as a measure of total spending in the industry and decompose it by income and education groups using CEX-based shares. This approach parallels Lebow and Rudd (2003) who show that reweighting the CEX using BEA spending shares yields more accurate inflation estimates, correcting non-classical measurement error in the CEX (e.g., Garner et al. 2009).[60]

Column 1 of Table S1 presents summary statistics for our linked dataset with 170 final industries. We classify manufacturing, agriculture, and mining into goods and all other industries into services. For some analyses, we further classify goods and services into 24 and 15 subsectors, respectively, listed in Table S2. We next provide details on the CEX and the IO table.

Consumer Expenditure Survey. The CEX is a stratified household survey conducted by the U.S. Bureau of Labor Statistics that measures the universe of personal spending by households with over 600 detailed product categories. The CEX consists

[58]These data were made available by Schott (2008) and converted into NAICS industry codes by Pierce and Schott (2012). Trade flow statistics are available only for trade in goods. We therefore assign zero direct imports from specific trading partners in service industries. This does not constitute an important limitation for China and Mexico. For instance, China constitutes less than 3% of total U.S. imports of services according to the BEA International Services tables for 2007. This limitation is likely to be more important when considering trade with developed economies.

[59]We note that our analysis is fully consistent with the IO structure of the economy, such that the same industry may have both final and intermediate sales. By final industries we mean industries with non-zero consumption in the CEX, without a need to classify industries into different types.

[60]Measurement error in the CEX does not create biases for our results as long as it has the multiplicative structure proposed and justified by Aguiar and Bils (2015): there may be industry- and consumer group-specific biases but no interactions between them. Industry-specific biases are corrected by the BEA weights, while consumer-group-specific biases only result in a re-scaling of consumption across groups without systematic effects on the expenditure composition of each group.

of two separate parts, the interview and diary surveys, which we use in combination. Quarterly interviews cover the complete range of expenditures, whereas diaries focus on some categories, such as food and clothing, in much greater detail. The interview panel includes around 6,900 households per quarter, each surveyed for four consecutive quarters. Diaries are collected for roughly the same number of distinct households per year but capture only two weeks of consumption. We select categories of spending (UCC) from both surveys according to the Integrated Stub file provided by the BLS, so that they cover all categories without double-counting.

The key advantage of the CEX is that consumption structure can be measured separately for different groups of households. We split households by bins of household income before tax, converted to the 2007 prices using the U.S. Consumer Price Index.[61]. As a measure of income, we use variable `FINCBTXM` in the interview survey and `FINCBEFX` in the diary survey. Eleven income bins are defined by the following cutoffs (in $000): 10, 20, 30, 40, 50, 60, 75, 90, 110, and 150. For the analysis in Section 5, we also split the households into deciles of earnings, with thresholds, in $000, of around 13.5, 21, 28.8, 37.3, 47.0, 58.7, 73.0, 92.5, and 127.4. We further split panelists by education of the household's reference person answering the interview (variable `EDUC_REF`), defining college education as bachelor's degree or higher. For Figure S5, we also the following variables: the mean age of the household heads (`age_ref` and `age2`), Census region (`region`), home ownership (`cutenure`), and family size (`fam_size`).

To increase the sample size, we combine data from 2006–2008. We drop all households with reported income below $5,000 because of concerns about misreporting and temporary unemployment. Our final interview sample includes 87,238 household-quarters with average annualized spending of $34,976 (excluding diary categories), while the diary sample has 31,727 household-weeks spending $12,554 per household per year.

Expenditure on housing services requires special treatment. The range of CEX spending categories includes rents and mortgage interest, but not the mortgage principal payments. However, an addendum section of the interview survey provides information on the self-reported rental value of owned property. In our static setup that is the closest analog to annual expenditures on housing for home-owners, so we

[61]Source: FRED database, https://fred.stlouisfed.org/series/CPALTT01USA661S.

add imputed rents to the set of UCC we consider. Aguiar and Bils (2015) follow a similar approach.

We build a manual concordance from 668 CEX consumption categories into 170 IO industries. We thank James O'Brien for providing us with the concordance between CEX interview categories and the 2012 version of NAICS from Levinson and O'Brien (2017). We use this concordance, converted into 2007 IO codes, as a starting point. We manually extend it to diary categories as well as missing interview ones. The concordance is many-to-one, with a few exceptions where we allocate CEX consumption by each group equally across the corresponding IO codes. In most cases, our concordance is consistent with, but much finer than, the concordance from CEX to NIPA personal consumption expenditure categories provided by the BLS and used by Buera et al. (2018) and Jaimovich et al. (2015), among others.

BEA Input-Output Table. We use the most detailed IO table for the U.S., which is available in 2007. While BEA publishes annual tables with 71 relatively coarse three-digit industries (which we leverage in Figure S6), the 2007 one is disaggregated into 389 six-digit industries. These industries are groups of six-digit NAICS codes: while NAICS includes 581 goods and 565 service industries, the IO classification includes 258 and 122, respectively, plus 9 special industries such as government and non-comparable imports. Some IO industries are as detailed as NAICS (e.g. Electronic computer manufacturing), but in other cases aggregation is quite strong (e.g. 24 NAICS codes within Apparel manufacturing become a single category).

We classify all industries into goods or services. Manufacturing, agriculture, and mining are classified into goods, while all other industries into services. Construction is sometimes viewed as a good-producing industry (Comin et al. 2021) and sometimes as a service industry (Cravino and Sotelo 2019). We treat construction as an industry ultimately providing shelter for households and businesses, therefore we classify it into services. Goods and services are further classified into 24 and 15 subsectors, corresponding to three-digit IO codes and two-digit NAICS codes, respectively. We assign Management and Administrative services (NAICS industries 55 and 56) to the subsector of Professional, Scientific, and Technical Services (code 54).

The use of the IO table is complicated by two considerations. First, the same product ("commodity") can be produced by different industries: for example, SUVs are manufactured by both SUV and car manufacturing establishments. We follow the standard procedure to address this issue by using the Supplementary Tables after Redefinitions (Horowitz and Planting 2009) and combining the Make and Use tables to produce a square commodity-by-commodity use matrix.

Second, distribution industries—wholesale, retail, and transportation—require special attention. BEA has two approaches for these industries, neither of which is fully consistent with our model. The standard "producer-value" table models the distribution margin (i.e., the cost of wholesaling, retailing, and transportation) as a flow going directly from the distribution industries to the buyers (whether final or intermediate); in this case, the data are aggregated across the various commodities that have a distribution margin. With this approach, it is not possible to see which group of consumers pays for retailing services (e.g., for the apparel they buy), which have low import shares. The import share of apparel, from the buyer perspective, has a large upward bias for the same reason. The supplementary "purchaser-value" IO table instead includes the distribution margin in absorption of each commodity, which resolves the problem under the proportionality assumption that domestic and imported apparel have the same fraction of retailing cost. Yet, this table is not consistent with the production side of our model. For instance, domestic apparel producers face very strong import competition, which occurs before both domestic and imported apparel is retailed.

We address these issues by constructing an "augmented" IO table which yields correct measures of exposure to trade for both consumers and producers. To do so, we create two versions for each industry. The "producer version" hires primary factors and purchases intermediate inputs, produces output, exports, and gets imported. Then, the entire value of domestic absorption is sold to the "purchaser version" of that industry, which also buys distribution services from the corresponding industries and sells the combined outcome to final consumers and to producer versions of industries using its output as an intermediate input. Only the distribution margin of exporting (e.g., wholesaling of exported goods) is recorded as direct exports of the distribution industries. All the formulas of our model apply to this IO table. Although import penetration and export shares are zero in purchaser industries, value added is zero there as well, so the labor market exposures can be computed using the augmented table. Similarly, the relevant measure of import shares is computed in purchaser industries, which is indeed where all final consumption is concentrated.

In constructing the augmented IO table, we use both the producer- and purchaser-value tables from the BEA. Moreover, to measure the distribution margin for domestically sold and exported goods by each commodity, we employ the Margin Details table separately published by the BEA. Unfortunately, that table does not distinguish between modes of transportation and types of retailing, which have different IO codes. Therefore, we aggregate those industries in the entire analysis, resulting in 381 industries instead of 389. We keep transportation industries 485000 (Transit and ground passenger transportation) and 492000 (Couriers and messengers) intact because they do not constitute distribution margins, as reflected by the fact that their producer and purchaser output values are the same.

S.2.2 Nielsen-Census Data

Overview. Consumer packages goods are goods typically purchased in supermarkets.[62] To estimate import shares for them by consumer group, we use detailed expenditure data from the Nielsen Homescan Consumer Panel (henceforth Nielsen) and match them to the confidential U.S. Census Bureau data on domestic production and imports at the firm level.

To measure the direct and indirect import share of each barcode, we find the product's manufacturer or distributor in the confidential U.S. Census data.[63] We proxy for a product's import share by the ratio of imports to total sales of the corresponding firm. This measure captures imports of both final products and intermediate inputs (except those imported through a domestic intermediary). It is also available for imports from China, NAFTA, and 34 developed economies specifically.

To implement this idea, we build a novel match between Nielsen barcodes and firms in the Census datasets, in three steps. We start by assigning barcodes in the

[62] The Nielsen data cover a set of products regardless of whether they were purchased in a supermarket or elsewhere. For discussions of the share of overall consumption covered in Nielsen, see Broda and Weinstein (2010), Kaplan and Schulhofer-Wohl (2017), and Jaravel (2019).

[63] While barcodes uniquely identify products, they are not informative about the country of origin, especially in the U.S. Although the first three digits identify the country in which the barcode was registered (Bems and Di Giovanni 2016), most foreign products in the U.S. have domestic barcodes. For some barcodes, the country of origin can instead be obtained from the product label (Antoniades and Zaniboni 2016; Auer et al. 2021). However, we are not aware of a possibility to automate collecting this information in the U.S., while manual collection is infeasible due to the massive number of products sold in the country. Neither of these approaches would also be informative about the indirect import share of domestic products.

Nielsen data to firms in the GS1 US database. GS1 is a non-profit organization than maintains the barcode system; to sell products in supermarkets, a manufacturer or a distributor has to purchase a block of barcodes from GS1. Each barcode can only be registered by one firm.

Next, we link firms in GS1 to Census Bureau's confidential Business Register (also called SSEL) by name and address. With a small fraction of exceptions, all firms in the GS1 data have a U.S. address—thus, foreign firms do not tend to register barcodes without an affiliate or an intermediary in the U.S. In turn, SSEL provides a comprehensive list of names and addresses of U.S. firms and establishments. We develop a set of consecutive rules for exact and fuzzy matching and verify match quality by manual inspection of a sample of firms.

We finally link SSEL firms to the quinquennial Economic Censuses from 2007 and 2012 and the transaction-level data on imports and exports of goods from the U.S. Customs (LFTTD) using unique firm identifiers. From the Economic Censuses we obtain the total value of a firm's sales, while LFTTD yields the total value of its imports. Dividing imports (overall or by trading partner) by sales, we get our measure of the import share. In this process, we use all Economic Censuses, including Censuses of Wholesale, Retail, and other sectors, and not just the more commonly used Census of Manufactures. Observing non-manufacturing firms is useful for us, as importing of final products is often done by wholesalers and retailers.[64] To reduce noise, we pool three years of the Nielsen data, 2006–2008 and 2011–2013, for each Economic Census year. Overall, out of the total number of 23,300 Nielsen firm-years, we successfully match 12,700, covering 83% of sales.

We adopt a square-root weighting scheme to reduce measurement error. As we cannot attribute a multi-product firm's imports to a particular product it sells, or even to consumer packaged goods overall for firms operating in multiple industries, our proxy for the import share is likely to be noisier for large firms. Large multi-product firms play a large role when measuring the share of import spending by consumer group, a consequence of "granularity" in firm-level datasets (Gabaix 2011). Our solution, similar to Caron et al. (2014), is to reduce the influence of large firms by rescaling each firm's Nielsen sales to its square root and adjusting expenditures

[64] In Appendix S.2.2, we track several products photographed in a Walmart store to verify that domestically produced goods are normally registered by the manufacturer, while imported products are registered by the distributor, often a wholesaler.

on its products by each consumer group proportionately.[65]

Column 2 of Table S1 presents summary statistics for the linked dataset, while Table S7 details them by the three product classes. The average import share is 11.1%, similar to the entire consumption basket reported in Column 1, but there are large differences across product classes. We next provide details on the data sources, the matching process, and present further match statistics and examples.

Data sources. The Nielsen company asks around 55,000 U.S. households per year to record all purchases within certain classes of products. Consumers scan purchased goods using handheld barcode scanners provided by Nielsen. They also manually enter products that do not have barcodes, such as fresh produce. Nielsen obtains price information from a combination of store data and manual entry by households. The stratified sample of households is representative of the U.S. population in terms of income, education, age, race, household size, and other characteristics when using the Nielsen-provided projection weights.

GS1 maintains the concordance between barcodes and firm names and addresses; the version we obtained is complete as of February 2016. We drop 5.2% Nielsen barcodes which we could not link to GS1 (they constitute 1.8% of total sales in Nielsen). In most cases GS1 firms are located within the U.S., although there are some exceptions, mostly with Canadian addresses. We drop firms with addresses outside 50 U.S. states and Washington, D.C. or with missing state information, which constitute 4.3% of all Nielsen firms but only 0.75% of total sales.

We use three data sources on the Census side. Business Register, or SSEL, is the comprehensive list of establishments, with names and addresses, assembled using Census surveys, Internal Revenue Service tax data, and other data sources at the annual frequency (DeSalvo et al. 2016). Because firms change names and addresses over time, while GS1 provides only one observation per firm, we use addresses in the SSEL for all years from 1991–2014, which improves the quality of the merge.

The Economic Census is the survey of all business establishments in the U.S. It is conducted by the Census Bureau in years that end with 2 or 7, and participation is

[65]Granularity is a substantial challenge: in the full Nielsen sample, top 50 firms capture 46% of sales in an average year; with square-root weights, they take up only 9%. In unreported results we verify that all findings are very similar, both qualitatively and quantitatively, when firms are weighted by their Nielsen sales to the power of 1/4 or 3/4, or by the square-root of the firm's sales in the Economic Census.

required by law. The content of the questionnaire varies across sectors and industries but all of them include questions on the total revenue. We primarily use Censuses of Manufactures, Wholesale, and Retail. Establishments in Services, Finance, and Utilities are also part of our Economic Census sample, but they are rarely matched to Nielsen.

Finally, LFTTD (Linked/Longitudinal Firm Trade Transaction Database) is the microdata on all international trade transactions, based on the import declarations and shippers export declarations. It has been matched to the Census by firm identifier (see Bernard et al. 2009).

Sample construction. We predict total sales of each Nielsen barcode by applying projection weights provided by Nielsen to the purchases by each household and, using the GS1 crosswalk, aggregate them to firms and firm-by-product module cells. We classify households into college- and non-college by using education of both male and female heads. If they are both present but only one has college degree, we attribute half of the purchases to each education group. Income is reported in 16 discrete bins, and we use their midpoints.[66] Income is reported with a two-year lag, so we use the value from two years after, whenever available.

We apply several filters to Nielsen. First, we drop households with reported income below $5,000. Second, we drop "magnet data"—products that do not use standard barcodes, such as fresh fruits and vegetables. Finally, we also drop firm-years with less than five unique barcode-household pairs and those with total unweighted spending by Nielsen panelists under $100—we label those as "tiny" Nielsen firms. From now on, we will suppress mentioning years.

We then compute import shares for each Census firm. The numerator is total imports from LFTTD. To measure the total firm output in the denominator, we aggregate revenue of all establishments belonging to the firm. However, this creates double-counting if a manufacturing company ships its products to its own wholesalers or retailers and then sells them. Therefore, we only count the total revenue in the largest 2-digit NAICS sector in which the firm operates, although the results are not substantially different without this correction. We drop firms for which imports

[66] The cutoffs in $000 are: 5, 8, 10, 12, 15, 20, 25, 30, 35, 40, 45, 50, 60, 70, and 100. In some years, the top-income group is decomposed further, but we use a consistent classification. We assign the top-income group the value of $140,000, based on the average income in the years when we have more detailed data.

exceed 200% of annual sales, indicating an imperfect match between LFTTD and the Census.

Finally, we merge name and addresses in GS1 with the Census firms—a procedure we describe next. Once done, we implement a consistency filter. Some firms, particularly large ones, span many industries, so their scope may not be covered well by the set of products covered by Nielsen. As a result, the overall importing behavior may be a very bad proxy for the set of products covered by Nielsen. We therefore require that Nielsen sales of a firm are within the range of 1% and 300% of the Census sales. Although still wide, this range excludes strongest violations of consistency in both directions and makes our results robust to using the square-root of Nielsen or Census sales as weights.

Merging process. We match names and addresses between GS1 and each year of SSEL from 1991–2014 separately. The process consists of three steps. First, we pre-process names and addresses in both datasets to maximize the probability of exact matches. Second, we develop a series of matching rules and apply them starting from the strictest, giving priority to multi-establishment Census firms. Third, because names and addresses change over time, some matches will only be found in some years. We extrapolate them to other years whenever possible. We now describe each step in detail.

Pre-processing. We use the algorithms from the `reclink2` package from Wasi and Flaaen (2015), with minor modifications. For company names, the `stnd_compname` command removes special symbols, makes standard substitutions (e.g., INTL to International), and isolates the entity type (e.g., INC) into a separate variable. Pre-processing of addresses is particularly important. The `stnd_address` command parses them into several parts: the main address variable (where special symbols are removed, street types are converted to their abbreviations, e.g., Street into ST, etc.), as well as the post office box, unit (e.g. SUITE 1400), and building numbers, if present. We implement an important addition to this parsing procedure by also extracting the house number from the address. We define it as the number at the beginning of the address or, if the address starts with a letter, the largest number in the address.[67]

Matching algorithm. The SSEL consists of records of three types: multi-unit (one per establishment for firms with multiple establishments), "submaster" (one per tax identifier of a multi-unit firm, created for consistency with the IRS), and single-unit. We give priority to multi-unit and submaster records by first attempting to match GS1 firms to them. For GS1 firms that are still not merged, we try matching to single-unit firms that are part of the LBD (the Longitudinal Business Database, which links SSEL records across years). The lowest priority is given to single-unit firms outside of the LBD.[68]

Within each priority level, we apply consecutive matching rules, starting from the strictest one. Once a GS1 firm finds an SSEL match, it is removed from the process. This guarantees that each GS1 firm is matched to only one Census firm, except for rare cases when we find several matches using the same matching rule. At the same time, we allow several GS1 firms to be matched to the same Census firm, as should be the case for subsidiaries of the same firm that appear in GS1 separately.

We developed seven matching rules by trial and error and manually checked samples of matched firms to verify that each of them mostly produces correct matches. Each rule requires an exact match and non-missing values for some key variables, an exact match on additional variables where missing values are allowed, and a bigram probabilistic ("fuzzy") match on other variables with a specified match score threshold. The implementation is again based on the `reclink2` package from Wasi and Flaaen (2015). While we kept its logic, we substantially improved computational efficiency in our own `reclink4` command.

Table S8 lists the rules. The two strictest rules require a non-missing match for the 9-digit zipcode (ZIP+4). Although available only for some firms, it generally identifies the building or a post box precisely. The first rule additionally requires an exact (possibly missing) match for the firm name, house number, address, PO Box,

[67]Extracting the largest number is inspired by the the addresses of foreign firms are treated in the LFTTD (see Kamal and Monarch 2016). With fuzzy matching, matching on the house number ensures that buildings like 47 Main St. and 49 Main St. are distinguished. It is also very useful for parts of Wisconsin and Illinois which use alphanumeric addresses, e.g. "W190 N10768 Commerce Cir, Germantown, WI."

[68]One SSEL record may list up to two addresses per establishment (physical and mailing) and sometimes specifies two zipcodes (one reported and one inferred automatically based on the rest of the address). We use all available versions of the address to increase the probability of the match.

unit, and building, standardized as previously described, while the second rule only requires an exact match on the house number, while the other variables are matched in a fuzzy way. The least restrictive seventh rule requires exact matches on the firm name, its entity type, and state, still delivering high quality of matches for the records that have not been matched using stricter rules.

Extrapolation of matches. Matching with GS1 is done separately for each year of the SSEL. If a GS1 firm does not find any SSEL match in a given year t, we turn to the matches that were found for this firm in other years, with preference to the closest years (starting with $t+1$, then using $t-1$, $t+2$, $t-2$, $t+3$, etc.). If some match is found in year t', we check in the LBD whether the matched firm existed in t and, if so, use this match for year t.

Match statistics. Panel A of Table S9 shows that the majority of Nielsen firms, excluding tiny ones, is matched, covering over 83% of total Nielsen sales.[69] In 2007, there were 26,900 Nielsen firms, and elimination of the tiny ones leaves us with 11,000 without any significant loss in total projected sales. Out of them we are able to find a Census match in the same year of the Census Business Register for 7,600, while using names and addresses from other years adds another 600 firms, making it 8,200 total. Although all firms are supposed to fill out Census forms, not all of them do, so we find 7,200 Nielsen firms in at least one of the Censuses, and of them 6,100 pass the consistency filter. Although there are a few cases where we find two Census matches for the same Nielsen firms, the number of Nielsen firms with single matches is the same 6,100 after rounding. Statistics are similar for 2012, increasing the sample size to 12,700 firm-years.

Panel B of Table S9 shows merging statistics starting from Census firms. Since Nielsen only covers consumer packaged goods, we do not expect a high match rate in most industries. However, Nielsen coverage is strongest for food, alcohol, and tobacco. This panel starts from all 51,500 firms in the Census of Manufactures in the corresponding NAICS codes 311 and 312. Out of them, 8,900 (or 17.3%) are merged to any Nielsen firm, including the tiny ones, and the merged ones account for 79% of the total sales. After dropping small Nielsen firms and implementing the

[69] The match rate is above 83% of sales for food and health and household products, but a bit worse for general merchandize, at 76%.

consistency filter, we match only 9.3% of the firm count but still 58.7% of sales by all manufacturers in the industry. Note that we also merge many wholesalers and retailers selling food, not accounted for in this table.

Table S10 shows that multi-establishment firms are a minority in the matched sample (29%), but they cover 93% of sales. Within both multi- and single-establishment matched firms, the strictest matching rule 1 captures the largest share of firms, but all rules contribute to the sample.

Table S11 shows the fractions of firms operating in different sectors, defined by their 2-digit NAICS codes, in the sample.[70] The manufacturing sector constitutes the largest fraction of the sample (57.2% with square-root weighting), followed by wholesaling (29.0%) and retailing (8.7%). The smaller share of retailers is in part determined by their large average sales, which imply that the square-root weighting scheme reduces their importance. At the same time, it is important to understand that most products sold by retailers are registered by other firms. We discuss below examples of products showing that this is true even for products manufactured for and distributed exclusively by Walmart. Among the 3-digit NAICS codes, Food Manufacturing and Nondurable Goods Wholesalers are the most prevalent ones, followed by Chemical Manufacturing (which includes soap, shampoos, etc.) and Beverage and Tobacco Manufacturing.

The last column of Table S11 presents a nice test on the quality of the match. Nielsen data allow us to identify products that are branded by the retail chain that sells them ("private label brands"). We find that over 99% sales of barcodes registered by food and beverage stores, according to their main NAICS code in the Economic Census, are private label brands. For comparison, this share is only 7.9% for wholesalers and mere 1.2% for manufacturers.

Table S12 examines how representative the matched sample is. Panel A compares firms in Nielsen, excluding tiny ones, that found a match to those that did not. Median firms in the merged sample have about twice as large Nielsen sales relative to the firms that did not find a match. Matched firms also sell to slightly, but statistically significantly, poorer and less educated consumers. For example, 29.1% of sales of matched firms is to college graduates, as opposed to 30.7% for firms that

[70]Because Census data provides NAICS codes for establishments not firms, we classify firms by the 2- and 3-digit NAICS in which they have the largest payroll, excluding NAICS code 55 "Management of Companies and Enterprises".

we did not match. However, these differences can largely be explained by the size difference; they are reduced when controlling for a quadratic term in log Nielsen sales. Panel B provides evidence on sample selection for the firms in the Census of Manufactures producing food, alcohol, and tobacco. Again, merged firms are much larger, with median sales of $13.3 million, payroll of $1.9 million and 54 employees, as opposed to $606,000 sales, $113,000 payroll and 4 employees for a median Census firm that we did not merge. Comparing these sets of firms by skill intensity (the payroll share of non-production workers) does not reveal statistically or economically significant differences.

Examples. A few examples illustrate the way in which our Nielsen-Census linked dataset labels products as domestic, imported, or as using imported intermediate inputs. We visited a Walmart store and photographed a sample of products, which we identify as domestic and imported by looking at their labels. Then, we identified these products in the GS1 database using their barcodes and searched for the information about the firms that registered them on the Internet. Figure S15 shows pictures of five products that illustrate well different situations we observed.[71]

Panels A and B show two plates labeled as "Made in the USA"; one is from an independent brand and the other is distributed by Walmart. According to the GS1 data, they were respectively registered by World Kitchen, LLC and Merrick Engineering Inc.. An Internet search shows that both of these companies are U.S.-based manufacturing firms, so our Nielsen-Census linked dataset will label them as domestic products (unless these companies use a lot of imported intermediate inputs).

The three other products on Figure S15 are all imported. The bed sheets in Panel C belong to the same brand as the plates in Panel B, they are distributed by Walmart, but their label indicates "Made in China". In GS1, we see that their barcode was registered by Jiangsu Royal Home USA, Inc. Internet sources indicate that this firm belongs to the NAICS code 423220 "Home furnishing merchant wholesalers" and imports its products from China. Our Nielsen-Census linked dataset will therefore label this product as imported.

The plates in Panel D, also made in China, are registered by First Design Global, Inc, which (again, according to Internet search) is a U.S.-based manufacturing firm

[71] We have not used any Nielsen or Census data in this section. These products may or may not be in our final sample.

but imports tableware and kitchenware from China. We will therefore attribute these plates partially to imports, using as a proxy the ratio of imports to total sales for this firm. This proxy does not bias our estimates of the expenditure channel if there is no systematic correlation between import shares and buyer characteristics within firms.

Finally, the Canadian hair conditioner from Panel E is distributed by Walmart and, unlike the aforementioned products, was registered by Walmart itself. Therefore, in the Nielsen-Census linked dataset, we proxy for the probability that it is imported by the fraction of Walmart's direct imports relative to its total Census sales. This may be an underestimate if Walmart's direct imports in the Customs data mostly cover its own-registered products, whereas its sales include all products, e.g. those from all previous pictures.

S.2.3 Datasets for Motor Vehicles

Linked CEX-Ward's dataset. To measure purchases of motor vehicles by consumer group, we use the OVB file ("Owned Vehicles Detailed Questions") from the CEX Interview Survey, which asks respondents to provide information about all vehicles they own, including the brand, whether the vehicle was purchased new or used, and in some cases the price. The respondents are asked to list all types of vehicles, but we focus on cars and trucks (which are mostly light trucks, i.e. SUVs, although in some cases could be medium-duty trucks as well), excluding motorcycles, boats, etc. As previously, we classify households into groups according to bins of household income or to the college education of the respondent after converting income to the 2007 prices as in Appendix S.2.1.

The data are available since 2006 but we use it for 2009–2015 for consistency with the Ward's sample. Each household is expected to participate in the survey for four consecutive quarters, so to avoid duplication we only use the most recent survey in which the OVB survey is filled. If the household reports several vehicles in that survey, we use all of them. Like in other datasets we build, we drop vehicles owned by households with income before tax below $5,000.

Data on importing come from Ward's Automotive Yearbooks. We use the electronic versions of the 2011, 2013, 2014, and 2016 yearbooks. Each of them shows the statistics for the previous two years, thus covering the entire 2009–2015 period. In each year we use five Ward's tables. Two are on sales in the U.S. (U.S. Car Sales by

Line by Month and same for Light Trucks): for each model (also called "lines," e.g. Chevrolet Camaro) they decompose the number of cars and light trucks sold in the U.S. into those built within and outside NAFTA. The other three tables (U.S. Vehicle Production by Line by Month and same for Mexico and Canada) report production by country and model, allowing us to decompose vehicles assembled within NAFTA into those built in the U.S., Canada, and Mexico.

We define a model as imported if it was assembled outside of the United States. Most models are either only imported or only assembled domestically, but in a few cases assembly occurs both in the U.S. and abroad. In such cases, we classify the model as "partly imported": our proxy for its direct import share is the fraction of vehicles of this model that were assembled outside the U.S. We then aggregate models to brands with total U.S. purchases as weights.

Specifically, we first aggregate all years of Ward's data to measure, for each model, the number of vehicles sold in the U.S., the share assembled outside NAFTA, and the shares of assembly within NAFTA that comes from the U.S., Canada, and Mexico separately. We then compute the domestic share of each model sales as the product of those from within NAFTA (from tables on sales) and the share of U.S. within NAFTA production (from production tables). For one model only (BMW Z4), the sales table reports some NAFTA production, but production data are missing, in which case we checked the country of production manually. At the end we aggregate all models by brand using sales weights from Ward's.[72]

We dropped a small fraction of CEX purchases for brands that we do not observe in Ward's because their production was discontinued before 2009. Oldsmobile is the most frequent brand we have to drop. All dropped brands combined constitute less than 1.5% of the sample. We also keep four brands (Daewoo, MG, Austin-Healey, Zenn) which are in CEX but not in Ward's, and are fully imported. This results in the sample of 45 brands, listed in Table S3. Column 3 of Table S1 presents summary statistics.

[72]We attribute all imports from countries other than NAFTA to the 34 developed economies. Ward's data do not report origin countries for cars imported from outside NAFTA. However, according to the BACI database on bilateral trade flows, out of all U.S. imports of motor vehicles (HS code 8703) in 2009–2016 from outside NAFTA, less than 3% were countries other than our 34 (mainly from South Africa).

Linked CEX-Census dataset. Import shares constructed with the CEX-Ward's dataset do not include imports of intermediate inputs used to produce domestically assembled vehicles. To address this potential limitation, we match the CEX to the confidential Census of Manufactures and LFTTD, where the fraction of imported car parts in the value of manufacturer's sales can be measured and compared to the value of imported assembled cars. This requires aggregating the CEX data from brands to firms.[73]

We use the 2012 version the Census of Manufacturers and the Customs data for the same year. We match these data to expenditure shares from the CEX. To increase sample size, we use all years of the CEX when the brand variable is available, from 2006 to 2015. In this analysis, we include cars only, not light trucks.

To match domestic car producers in the CEX, we first link each car brand to the firm that owned it in 2012, using the Ward's Automotive Yearbook and Internet search. Then we manually search for firm names in the 2012 Business Register (SSEL)—the list of all establishments in the U.S., and obtain the firm identifier or identifiers for all firms that participated in the Census.

Our sample includes two types of observations. If a firm has no production in the U.S., we keep its brands separately and assign 100% imports, both direct and total. And if a firm has some U.S. production (and participated in the 2012 Census of Manufacturers),[74] we aggregate its brands together and measure import shares.

The value of imports of assembled cars is defined as total imports in the Customs data in the Harmonized Trade Classification (HS) code 8703 "Motor cars and other motor vehicles principally designed for the transport of persons".[75] Imports of car parts are defined as those in HS codes 8706 (chassis fitted with engines), 8707 (bodies for motor vehicles), 8708 (parts and accessories of motor vehicles), 84 (machinery), 85 (electrical machinery and equipment), 90 (measuring and other instruments), 39 (plastics), 40 (rubber), 73 (articles of iron and steel), 83 (miscellaneous articles of base metal), and 94 (furniture).

[73] The CEX-Ward's sample shows that there can be meaningful variation across brands within a firm: for example, the share of vehicles assembled abroad is about 20% for Buick and 40% for Chevrolet, which are both produced by GM.

[74] Participation in the quinquennial Census is required by law, so the vast majority of firms reply. However, not all of them do, and the information on participation is confidential.

[75] This HS code includes some vehicles besides cars (e.g. SUVs and ambulances), which may create some upward bias.

We measure car sales by the sum of total shipments of domestically assembled cars and the imports of assembled cars. The former is defined as the total value of shipments from all of the firm's establishments which belong to NAICS code 33611 (Automobile and light duty motor vehicle manufacturing) in the Census of Manufactures. Then the direct (total) import share is the ratio of imports of cars (cars plus parts) in car sales. Note that while we use counts of vehicles in the CEX and Ward's data (due to data availability), here import shares as defined by value.

S.2.4 ACS Data

To measure the composition of workers by industry, education, and earnings, we use the 2007 American Community Survey from IPUMS — the long form of the population census answered by a random 1% sample of the U.S. population every year (Ruggles et al. 2015). We select only employed workers and drop the public administration sector. For the analyses of earnings, we rely on the `incwage` variable that captures total pre-tax wage and salary income during the previous calendar year; we only consider workers with earnings of at least $5,000. We split them into ten deciles, with the cutoffs, in $000, of 10.7, 16.0, 21.3, 27.0, 32.2, 40.0, 49.0, 60.0, and 85.0.

Since industries in ACS are more aggregated than IO codes (there are 253 codes overall, recorded in the variable `ind`), we have built a weighted crosswalk from ACS industries to IO codes. First, for each ACS industry we find the set of corresponding NAICS industries using a crosswalk provided by IPUMS.[76] Second, we allocate each ACS code to those NAICS industries with weights proportional to the total payroll by NAICS, which we obtain from the 2007 Quarterly Survey of Employment and Wages.[77] Third, we aggregate NAICS industries to IO codes. Finally, in parallel to our approach to the CEX (see Appendix S.2.1) we reweight the ACS to match the total compensation of employees by IO code from the IO table.

[76]Only in one case (NAICS industry 519130) the same NAICS code corresponds to two IND codes. We split this NAICS code into two proportionately to the IND payroll.

[77]The QCEW tabulations are published by the Bureau of Labor Statistics based on unemployment insurance statistics.

S.2.5 Estimation of Income Elasticities

Here we describe the procedure used to estimate income elasticities for each IO industry in Section 5, based on the CEX-IO data. Our approach uses the definition of the income elasticity as describing the relationship between spending and consumer expenditure (the Engel curve). As long as different consumers in the same country have the same preferences, face the same prices, and income elasticities $\psi_{xj} \approx \psi_j$ do not have much variation across income levels x, cross-sectional data allow us to estimate ψ_j directly. By taking this approach, we avoid making any parametric assumptions on the utility function and estimating demand structurally. Intuitively, higher-income consumers have larger expenditure shares on income-elastic products. Using this logic, we first compute the income *semi*-elasticity for each spending category by regressing spending shares on the logged total expenditure and then convert the estimates to elasticities and aggregate them into the IO industries.

Specifically, we split households in the CEX sample into 11 bins by the reported pre-tax household income and compute consumption shares across all spending categories (UCC) j for each of the bins i separately (s_j^i) and overall (s_j). Then for each spending category we estimate the income *semi*-elasticity by regressing, across income bins, spending shares on the log of total expenditure in this income group, averaged across households:

$$s_j^i = \text{constant}_j + \psi_j^{\text{semi}} \log \text{Expenditures}_i + \text{error term}_{ij}.$$

Observations are weighted by the number of households in each income bin. For an income-elastic spending category, the share is increasing in the total expenditures, so $\psi_j^{\text{semi}} > 0$, and the reverse holds for income-inelastic products. We then convert the semi-elasticity into the elasticity ψ_j for an average consumer of product j:

$$\psi_j = 1 + \frac{\hat{\psi}_j^{\text{semi}}}{s_j}.$$

The intermediate step with semi-elasticities guarantees that the spending-weighted average of income elasticities across all spending categories is equal to one, as it should be theoretically:

$$\sum_j \psi_j s_j = \sum_j s_j + \sum_j \hat{\psi}_j^{\text{semi}} = 1 + 0 = 1,$$

where $\sum_j \hat{\psi}_j^{\text{semi}} = 0$ because spending shares sum up to a constant (one) for each income group, and the regression of a constant on $\log \text{Expenditures}_i$ yields a zero slope.

Expenditures are used on the right-hand side instead of income because in the CEX, total expenditures do not vary one-to-one with reported income. That relationship is increasing but much less than proportionate, which may be a consequence of imperfect measurement of income—either because current income is not a good proxy for permanent income, or for pure measurement error reasons. In either case, income elasticity estimates would be biased towards one if income was used on the right-hand side.

We winsorize a small number of ψ_j to be between -1 and 3. At the end we convert the UCC-level income elasticities to IO codes in the same way as we do for the expenditure shares.

S.2.6 Ranges of Substitution Elasticities

Our Section 5 calibrations require four substitution elasticities: between domestic and foreign varieties (ξ_j), between goods and services (ρ), between industries within goods and services (ε_r), and the macro elasticity of substitution between college and non-college labor, σ_{macro}. In all cases we take prevalent values from the literature for the baseline analyses and consider intervals of values that cover many available estimates for robustness.

Our baseline value for ξ_j is 3.5 in all six-digit industries, which is equivalent to a trade elasticity of $\xi_j - 1 = 2.5$. In robustness checks we consider values of ξ_j between 1.9 and 5.1 and also allow ξ_j to vary across three-digit IO industries according to the estimates from Broda and Weinstein (2006). Our baseline value is near the median elasticity of 3.7 reported in Broda and Weinstein (2006) for ten-digit industries, and of 3.4–3.7 in Soderbery (2015) using the same Broda-Weinstein method but for eight-digit industries and for different years of data, as well as near the mean of 3.6 in Ossa (2015). The range of 1.9 to 5.1 corresponds to the estimates from Soderbery (2015)'s LIML procedure and Simonovska and Waugh (2014), respectively. This interval also covers typical values of the elasticity of substitution between domestic and foreign varieties in Feenstra et al. (2018).

We set the elasticity of substitution between goods and services in consumption to $\rho = 0.6$, obtained from Cravino and Sotelo (2019). For robustness we consider the range between 0.2 and 0.85, as in Comin et al. (2021) (see also Cravino and Sotelo (2019)).

The elasticities of substitution between industries within each goods and services, ε_r, are more difficult to obtain (Dawkins et al. 2001; Costinot and Rodríguez-Clare 2015). As they are expected to lie between ρ and ξ_j, we set $\varepsilon_r = 2$ in the baseline analyses and consider values between 0.6 and 3.5. A recent paper by Redding and Weinstein (2017) estimated the elasticities of substitution between 6- and 4-digit NAICS industries to be 1.47 and 1.34, respectively. The estimate by Hottman and Monarch (2020) using 4-digit HS industries is 2.78. The range of elasticities we use covers all of these values.

Finally, for the calibration across education groups we set the macro elasticity of labor substitution to $\sigma_{\text{macro}} = 1.41$ from Katz and Murphy (1992). We check robustness to the range of $[1.41, 1.8]$, with the upper bound corresponding to the estimates from Acemoglu (2002) and Acemoglu and Autor (2011).

S.2.7 Counterfactuals Based on Observed Changes in Trade Costs

While our main analysis considered hypothetical trade shocks that are uniform across industries, here we consider the distributional effects of other counterfactuals based on shocks observed in the data. We calibrate the effects of three shocks to importing costs: the introduction of Trump tariffs in 2018 (on solar panels, washing machines, steel and aluminum products, and Chinese products), the observed change in tariffs between 1992 and 2007, and the observed change in "import charges" (defined as transportation and insurance costs) in the same period. We view tariffs as iceberg trade costs, ignoring tariff revenue.

The formulas in our model section capture the effects of a shock to importing trade costs of the same magnitude $d\log\tau$ for all imports from a set of countries c. A slight modification is necessary to capture a shock that varies across industries in proportion to some variable r_j, i.e., $d\log\tau_j = r_j d\log\tau$. Indeed, in this case the industry import price index (before IO adjustments) equals $(IP_{jc}r_j/IP_j)\,d\log\tau$ instead of $(IP_{jc}/IP_j)\,d\log\tau$. Thus, simply replacing IP_{jc} with $IP_{jc}r_j$ allows us to estimate the counterfactual changes of the equilibrium in the first order approximation. We describe below how c and r_j are defined for each of the three shocks we consider. In all three cases, we first measure the shock at the level of HS codes and then average it at the level of the corresponding IO code using the HS-NAICS concordance from Pierce and Schott (2012).

The first shock is the set of tariffs introduced by the Trump administration in 2018. We combine three sets of tariffs:

1. *Solar panels and washing machines.* Actual tariffs on solar panels and large residential washing machines have a complicated structure: their rates vary over time, they are combined with quotas, and certain exceptions are provided, as described in Presidential Proclamations 9693 and 9694 of January 23, 2018. We approximate these rates by using the base rates (30% for solar panels and 20% for washers) applied to the main HS codes described in the Proclamations and to all U.S. trading partners.

2. *Steel and aluminum products.* Tariff duties on imports of steel and aluminum by trading partners are given in Section 232 of the Trade Expansion Act of 1962. The tariff increases were proposed on March 1 and amended on May 31, 2018. We identify the steel and aluminum products that were affected by these tariff increases using the published lists of HS codes. We apply a 25% tariff on steel products, excluding imports from Argentina, Australia, Brazil and South Korea, and a 10% tariff on aluminum products excluding Argentina and Australia.

3. *China tariffs.* Tariffs on products imported from China were introduced according to Section 301 of the Trade Act of 1974. They were released by the Office of the U.S. Trade Representative in three tranches with different lists of products. The first two were finalized on June 15 and August 7, 2018, taxing approximately \$34bln and \$16bln (in terms of 2018 imports), respectively, with a rate of 25%. The third one, finalized on September 17, introduced a tariff of 10% on approximately \$200bln of imports.

The other two shocks we consider are the observed changes in (i) tariffs and (ii) import charges (transportation and insurance costs) between 1992 and 2007. We obtain data on both types of changes from the Census Bureau trade statistics made available by Schott (2008). For each IO industry and year, we measure the rate of tariffs t_j (or import charges c_j) as the share of total tariff duties (or total transportation/insurance costs) in total imports for personal consumption. For each industry j, the shocks are given by the change in $\log(1+t_j)$ and $\log(1+c_j)$ between 1992 and 2007.

The results are shown in Figure S11 and Panel B of Figure S12.

S.2.8 Census Data for Skill Intensity and Exports

To measure the relationship between skill intensity and exporting at the plant level (Table S6), we use Census microdata. We focus on the manufacturing sector because it is the only one where the information of the worker types is available and it is the most tradable sector.

Until recently, Census surveys did not ask establishments about education of their workers, which led to a long tradition to proxy for skill intensity by the payroll or employment share of non-production workers (e.g. Berman et al. 1994; Autor et al. 1998), who are considered to be more skilled than production workers (Berman et al. 1998). The situation has changed with the arrival of the 2010 Management and Organizational Practices Survey (MOPS) survey, which is a supplement to the Annual Survey of Manufactures (ASM), covering all largest firms as well as a sample of smaller ones.

We use MOPS questions 32–35, which ask for number of managers and employees, as well as the share of managers and non-managers with a college (bachelor) degree.[78] The shares are listed in terms of discrete bins, so we use the midpoints of those bins.[79] This yields an estimate of the share college graduates in total employment, $v^{\text{Emp}}_{\text{college}|j}$. Unfortunately we do not observe wages of college- and non-college workers. Therefore, to impute the payroll share we use the economy-wide average wages of these groups from the U.S. Census Bureau (DeNavas-Walt et al. 2011). They show that the median wage of college graduates is about 80% higher than that of non-college workers (considering individuals in the labor force and 25 years or older), so we measure the payrolls share of college graduates in each establishment j as

$$v_{\text{college}|j} = \frac{1.8 \cdot v^{\text{Emp}}_{\text{college}|j}}{1.8 \cdot v^{\text{Emp}}_{\text{college}|j} + \left(1 - v^{\text{Emp}}_{\text{college}|j}\right)}.$$

[78]The questionnaire is available at https://www2.census.gov/programs-surveys/mops/technical-documentation/questionnaires/mop-2010.pdf; also see Bloom et al. (2016). We drop observations where answers to any of these questions are missing.

[79]The bins are under 20%, 21–40%, 41–60%, 61–80%, and over 80% for managers and 0%, 1–10%, 11–20%, and over 20% for non-managers (we assign 25% to the last category).

It is very strongly correlated with $v^{\text{Emp}}_{\text{college}|j}$, so the details of imputation are not consequential. We then distribute each firm's total payroll to the two education groups according to these shares to compute the payroll-weighted average export shares by group in Table S6.

Besides the MOPS sample, we use the 2010 ASM and the full 2007 CMF, which report payroll to production and non-production workers directly. We match all of them to the Customs microdata (LFTTD) to measure export shares. Like Bernard et al. (2018), we do not use the CMF and ASM questions about plant exports, which are less reliable than direct observation of trade transactions. For firms with multiple establishments, we attribute firm exports proportionately to the value of establishment sales (shipments). We drop firms where exports exceed twice the total value of manufacturing sales, as those are likely to result from measurement error or other firm establishments which are not part of the sample (e.g. the non-manufacturing ones). We compute the export share of an establishment relative to the value of shipments.

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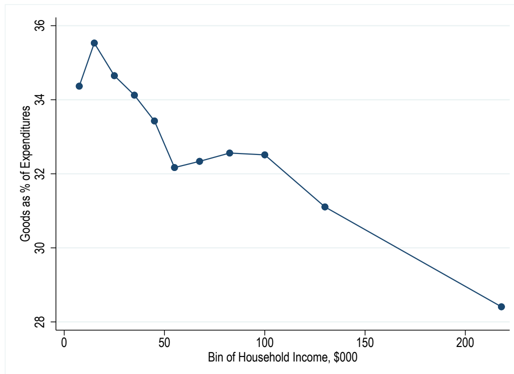
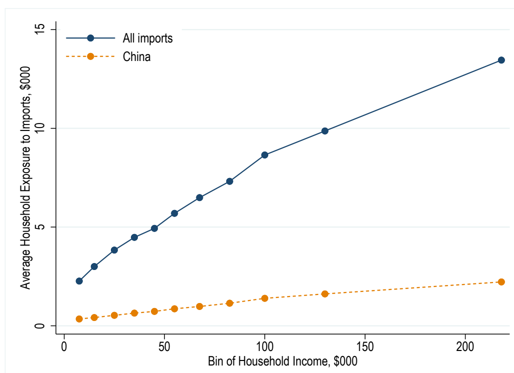
Supplementary Figures and Tables

Figure S1: Share of Spending on Goods across the Income Distribution



Notes: This binned scatterplot shows the relationship between household income and the share of (direct) expenditure on goods using industry-level CEX-IO data.

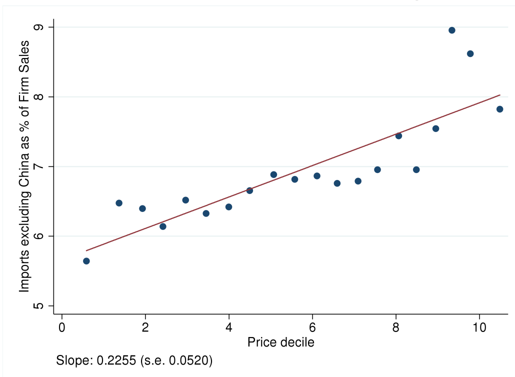
Figure S2: Average Import Expenditure in $1,000 by Income Bin



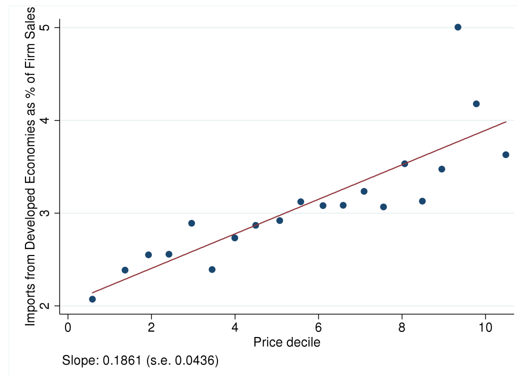
Notes: This binned scatterplot groups CEX panelists into 11 bins by household income before tax. The average value of total (direct and indirect) imports for each bin is reported, in $1,000, based on the industry-level CEX-IO data. The dollar value corresponds to the shares reported in Panel A of Figure 1, rescaled by the average of total expenditures for households within each bin.

Figure S3: The Role of Product Quality in Import Share Heterogeneity,
Nielsen-Census Sample

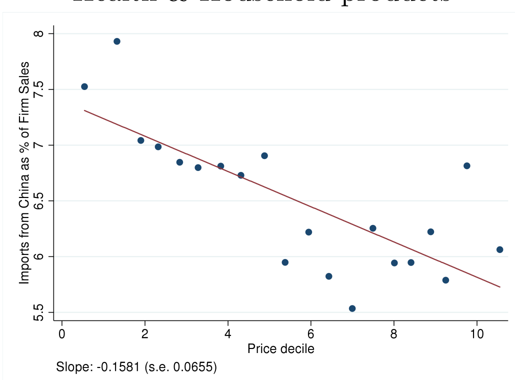
A: Prices and imports excluding China



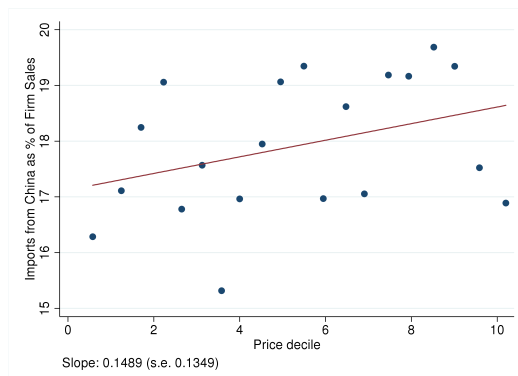
B: Prices and imports from developed economies



C: Prices and imports from China,
Health & Household products



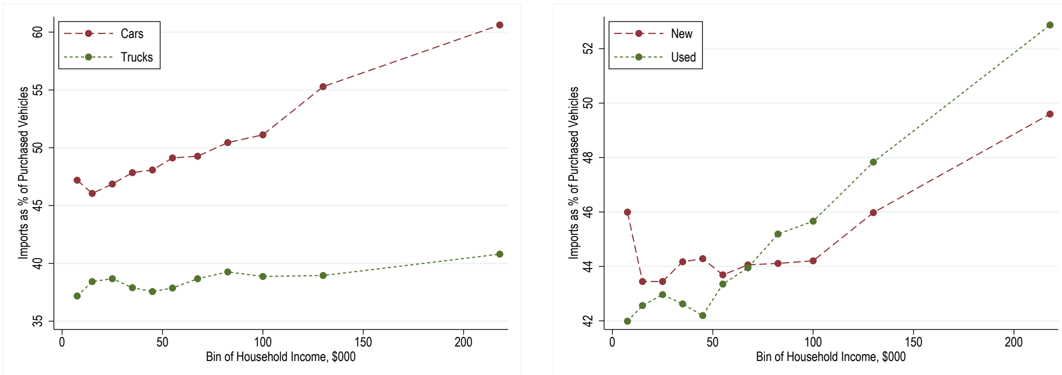
D: Prices and imports from China,
General Merchandize



Notes: These binned scatterplots report import shares by decile of barcode prices within product modules for consumer packaged goods. Import shares are computed at the firm level using the Nielsen-Census sample. Product modules which include barcodes with quantity measured in different units (e.g. ounces vs. counts) are decomposed by measurement unit. Firms are weighted by the square-root of their Nielsen sales, and weights are decomposed across barcodes of the same firm proportionally to sales. Fixed effects of modules by year are absorbed.

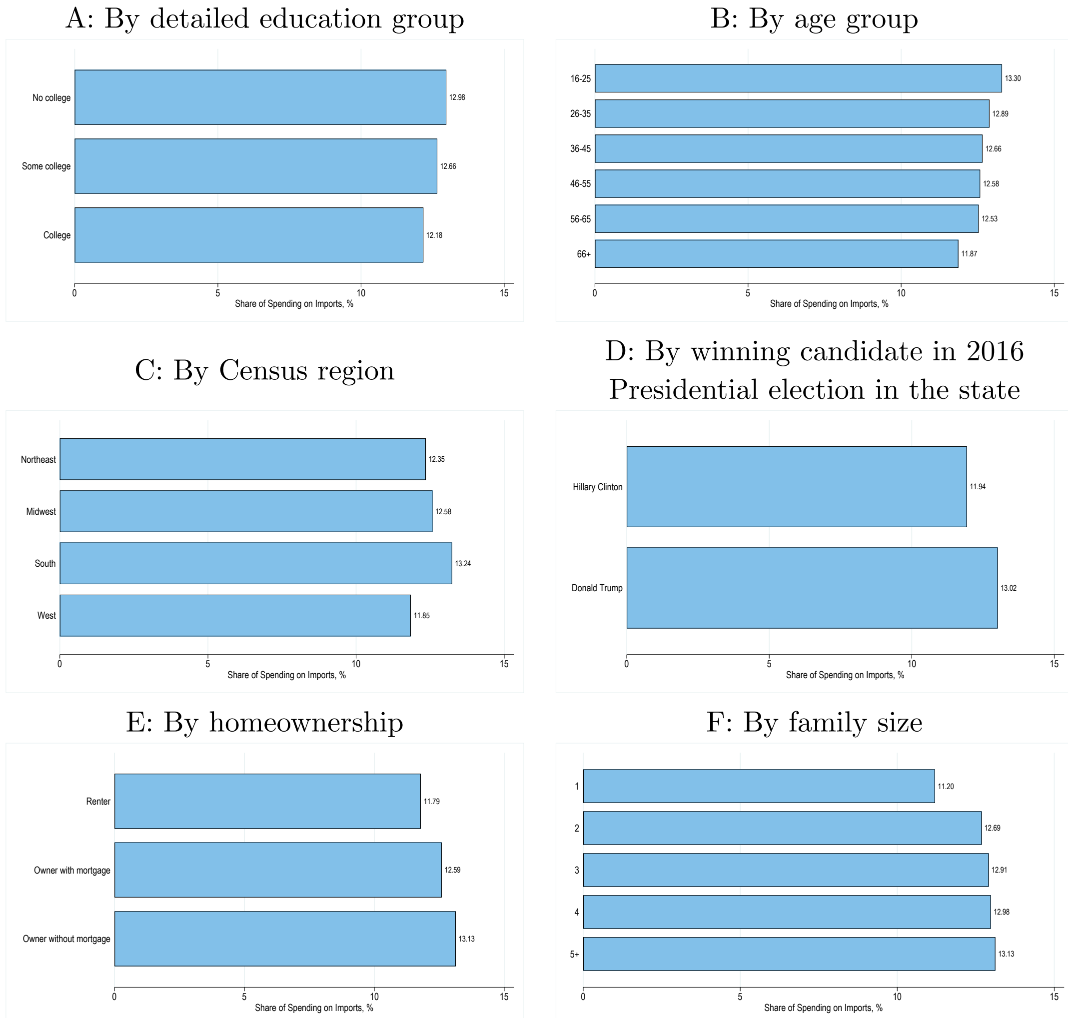
Figure S4: Imports Shares on Motor Vehicles by Subsamples

A: Cars vs. light trucks　　　B: New vs. used vehicles



Notes: Panel A reports average import shares for purchases of cars and light trucks separately Panel B instead splits the sample by whether the vehicle was purchased new or used, based on the CEX-Ward's data. Each vehicle in the CEX is assigned a probability of being imported, based on the average import share of the car brand in the Ward's data.

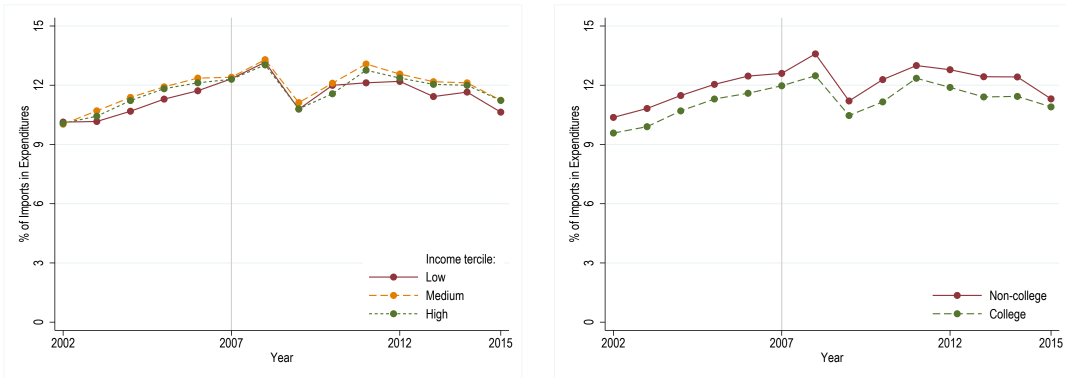
Figure S5: Import Shares across Other Household Groups



Notes: This figure shows fraction of spending on imports across groups of households, using industry-level CEX-IO data. Indirect spending on imports via imported intermediate inputs is taken into account.

Figure S6: Import Shares by Income and Education Groups over Time

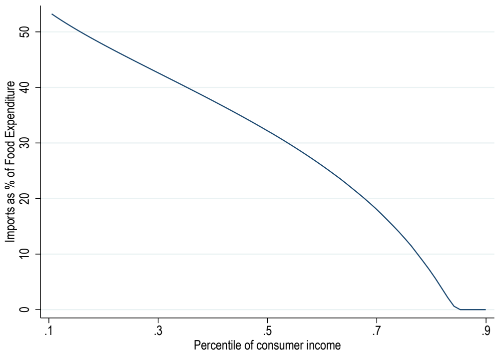
A: By income tercile   B: By education group



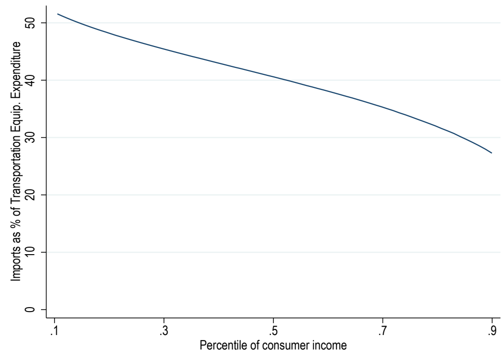
Notes: This figure shows the total fraction of imports in expenditures by demographic group (year-specific terciles of income before tax in Panel A and college education in Panel B) for 2002–2015. For each year, it combines the CEX Integrated Survey with the BEA Summary IO Tables after redefinitions. The methodology is analogous to that of Appendix S.2.1, except that IO industries are more aggregated. We use 73 three-digit commodities from the IO table and separate Non-comparable Imports from the Rest-of-the-World Adjustment. We drop used goods, rest-of-the-world adjustment, and government industries from the final calculation, which results in 71 industries, including 54 final industries matched to the CEX.

Figure S7: Additional Predictions of Fajgelbaum and Khandelwal (2016)

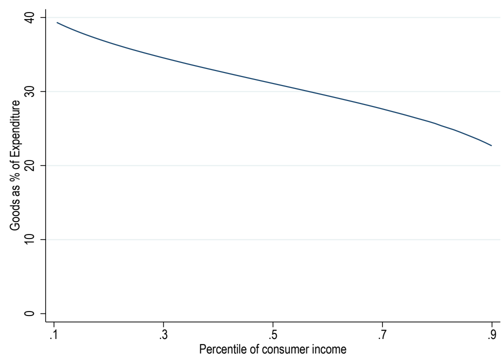
A: Imports shares on food



B: Import shares on transportation equipment

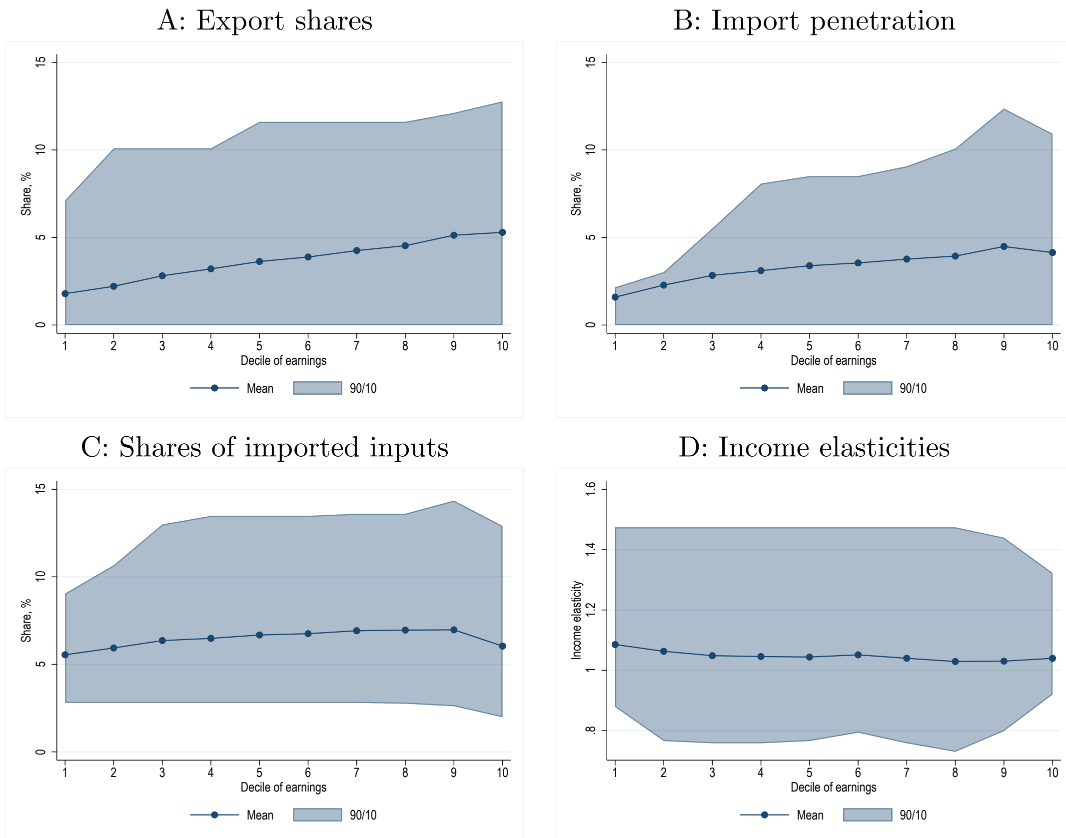


C: Goods as % of expenditure



Notes: This figure presents estimates of expenditure shares across the income distribution as in Fajgelbaum and Khandelwal (2016) for the U.S., using international trade data to estimate the parameters of the AIDS demand system. Panels A and B show the expenditure shares on imported varieties within spending on food (ISIC code 3, Panel A) and transportation equipment (ISIC code 15, Panel B). Panel C shows the fraction of goods (ISIC codes 1–16) in total expenditure.

Figure S8: Raw Worker-Level Exposure to Trade

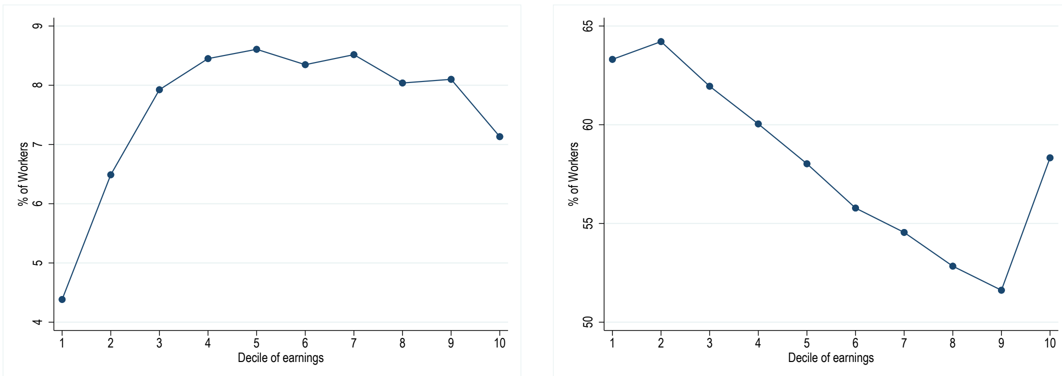


Notes: This figure plots "raw" exposure of workers to several margins of international trade, across and within deciles of initial earnings. Each worker's exposure is given by the corresponding industry variable, and no IO or other adjustments are applied. Each panel reports the average, the 10th percentile, and the 90th percentile across workers in each earnings bin.

Figure S9: The Share of Losers from a Fall in Trade Costs across the Income Distribution

A: In all industries

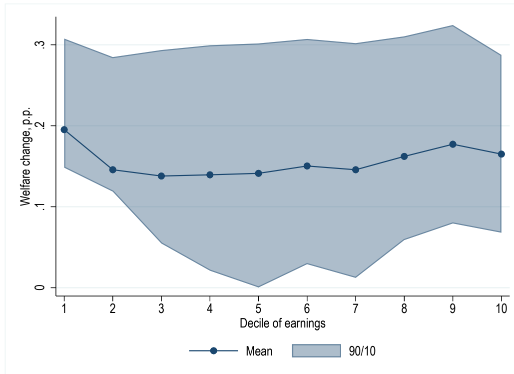
B: Goods-producing industries



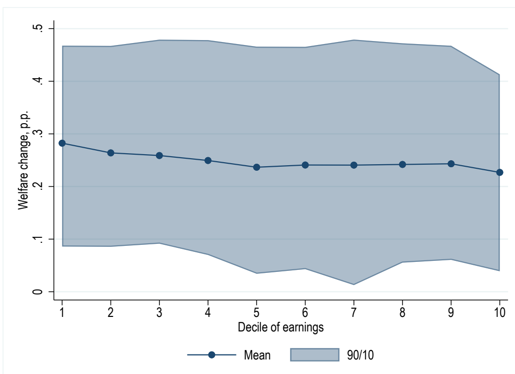
Notes: This figure reports the share of workers with negative equivalent variation in each decile, considering a uniform 10% fall in trade costs. The equivalent variation is computed using Proposition 2. Panel A considers all sectors, while Panel B focuses on goods-producing industries only.

Figure S10: Worker-level Welfare Effects of Trade Liberalizations with Specific Trading Partners

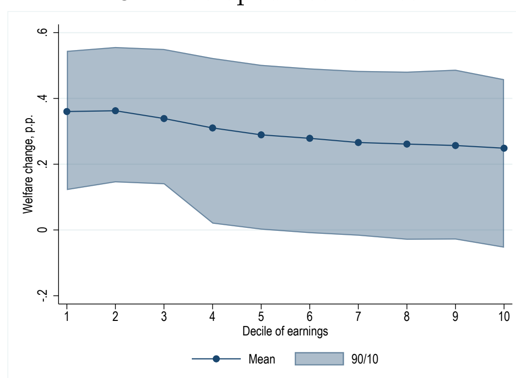
A: China



B: NAFTA



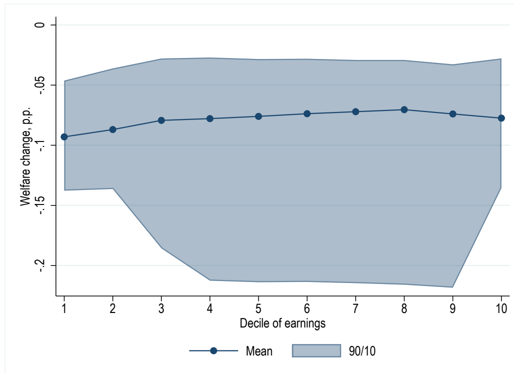
C: Developed economies



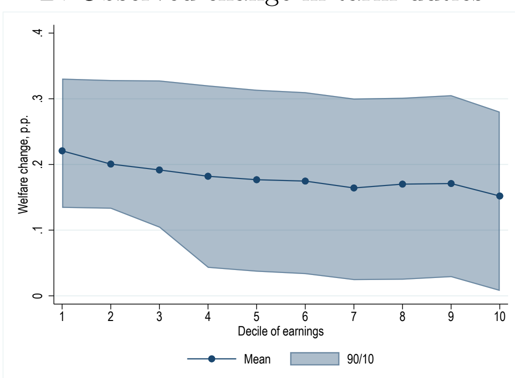
Notes: For the worker-level calibration of Section 5.3, this figure plots the welfare effects of a 10% fall in trade costs for goods imported from specific trading partners: China, NAFTA (Mexico and Canada), and 34 developed economies (OECD members, excluding NAFTA countries, plus Taiwan and Singapore). Each panel reports the average, the 10th percentile, and the 90th percentile across workers in each bin of initial worker earnings.

Figure S11: Worker-level Welfare Effects of Observed Changes in Trade Costs

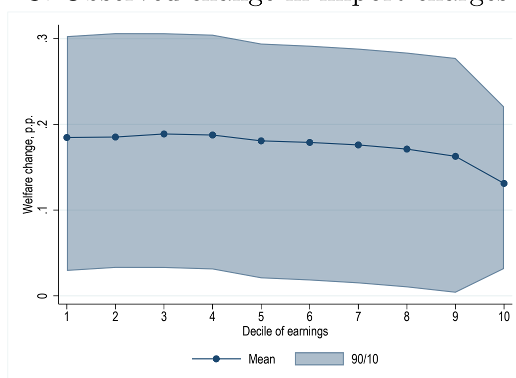
A: 2018 Trump import tariffs



B: Observed change in tariff duties

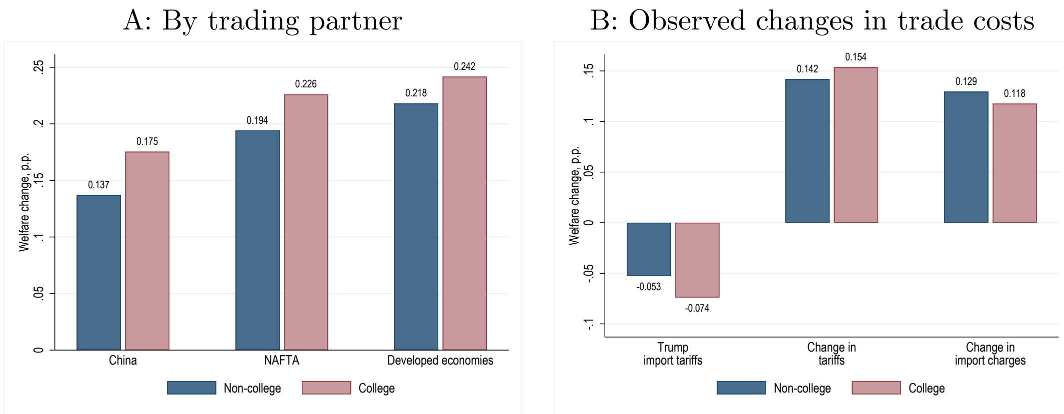


C: Observed change in import charges



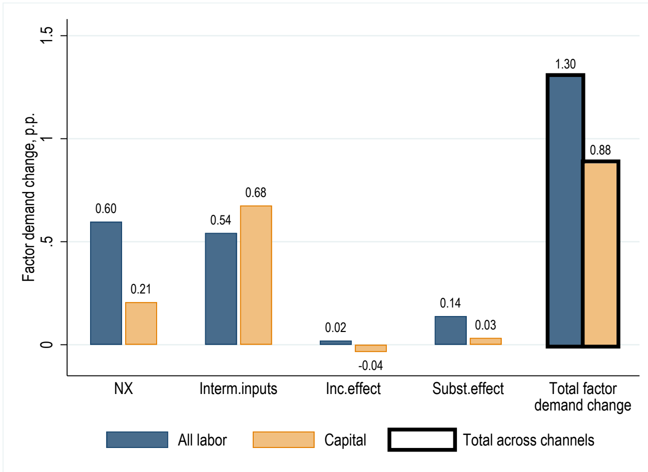
Notes: For the worker-level calibration of Section 5.3, this figure plots the welfare effects from observed shocks in the costs of importing goods. Panel A considers the introduction of trade tariffs by the Trump administration in 2018, Panel B studies observed changes in total U.S. tariff duties between 1992 and 2007, and Panel C examines the impact of changes in import charges (i.e., total transportation and insurance costs) between 1992 and 2007. Appendix S.2.7 describes the methodology.

Figure S12: Welfare Effects of Non-Uniform Trade Shocks across Education Groups



Notes: This figure plots the welfare effects from non-uniform trade shocks across education groups for the calibration of Section 5.4. Panel A considers a 10% fall in trade costs of importing goods from specific countries (China, Mexico and Canada, and 34 developed economies), while Panel B studies the effects of observed trade shocks: the introduction of import tariffs in 2018 by the Trump administration, changes in U.S. tariff duties between 1992 and 2007, and changes in import charges (i.e., total transportation and insurance costs) between 1992 and 2007. Panel A follows Proposition 2, while Appendix S.2.7 describes the methodology for Panel B.

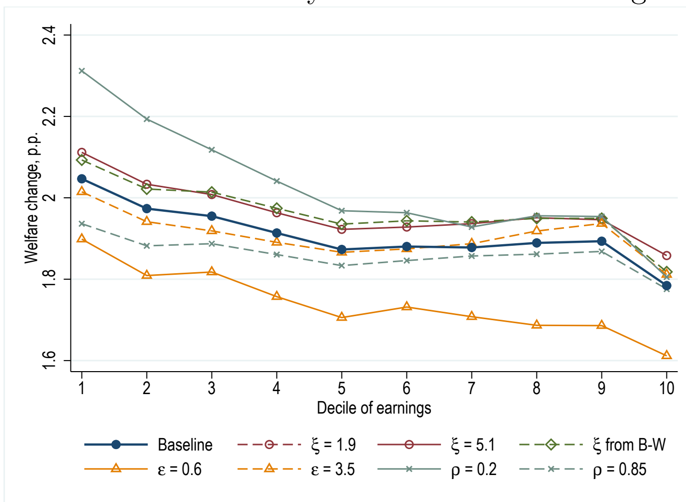
Figure S13: Changes in Factor Demand for Capital Owners and Workers for a Uniform Fall in Trade Costs



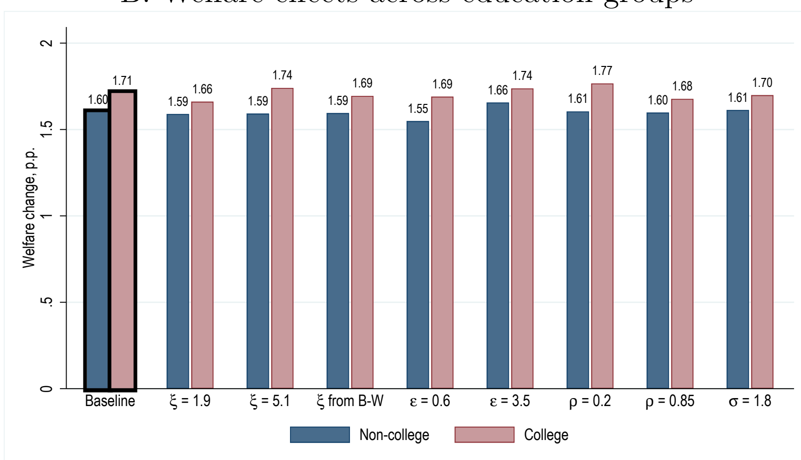
Notes: This figure reports the partial equilibrium change in factor demand for labor and capital for a uniform 10% fall in trade costs, decomposing the change into the several channels as in Proposition 2. The composition of industries in payments to capital owners is obtained from the "Gross operating surplus" row in the IO Table, similarly to how "Compensation of employees" is used for labor (Appendix S.2.4).

Figure S14: Robustness to Choice of Elasticities

A: Welfare effects by decile of initial earnings



B: Welfare effects across education groups



Notes: This figure reports the welfare effects of a 10% uniform fall in trade costs by worker groups, under different assumptions about the relevant elasticities of substitution. Panel A considers the worker-level calibration from Section 5.3, while Panel B focuses on education groups, as in Section 5.4. The baseline from Figures 6 and 7, reproduced here, uses the following elasticities of substitution in demand: across countries of origin within industries, $\xi_j = 3.5$; across industries within manufacturing or services, $\varepsilon_r = 2$; between manufacturing and services, $\rho = 0.6$. Panel B further uses the macro elasticity of substitution between workers with and without a college degree, $\sigma = 1.41$ (this elasticity is not relevant for Panel A). The figure then consider ranges of $\xi_j \in [1.9, 3.5]$, $\varepsilon_r \in [0.6, 3.5]$, $\rho \in [0.2, 0.85]$, and $\sigma \in [1.41, 1.8]$, capturing the values found in the literature (see Section 5.2). We also allow ξ_j to vary across 3-digit IO industries according to the estimates from Broda and Weinstein (2006), labeled "B-W" in the figure.

Figure S15: Examples of Products

<u>*Domestic products*</u>

A: Plates "Corelle"

UPC 071160 015449
World Kitchen, LLC

B: Plates "MainStays"

UPC 018643 157371
Merrick Engineering, Inc.

<u>*Imported products*</u>

C: Bed sheets "MainStays", Made in China

UPC 844178 030335
Jiangsu Royal Home USA, Inc.

D: Plates "Better Homes", Made in China

UPC 855602006 567
First Design Global, Inc.

E: Conditioner "Equate Beauty", Made in Canada

UPC 681131 124836
Wal-Mart Stores, Inc.

Notes: These products were photographed in a Wal-Mart store on September 16, 2017. Each barcode (UPC) is split by a space into the firm prefix in the GS1 database and the part which identifies the product within a firm. The country of origin (U.S., China, Canada) is from the product label, whereas the firm information is from the GS1 record corresponding to the barcode prefix.

Table S1: Summary Statistics

	CEX-IO (1)	Nielsen-Census (2)	CEX-Ward's (3)
Coverage	All goods and services	Consumer packaged goods	Motor vehicles
Product space	170 final industries	12,700 firm-years	45 brands
Spending share on imports, %	12.58	11.10	44.40
$\rightarrow$ China	1.93	4.15	0.00
$\rightarrow$ NAFTA	2.65	1.91	25.90
$\rightarrow$ 34 developed economies	3.21	3.10	18.51
Source of expenditures by consumer group	CEX, 2006–2008	Nielsen, 2006–08 and 2011-13	CEX, 2009–15
Source of import shares	BEA IO Table, 2007	Economic Census, LFTTD, 2007, 2012	Ward's, 2009–15

Notes: This table reports summary statistics for the three datasets on consumption and imports used in the paper. Column 1 describes the industry-level data, Column 2 the micro data for consumer packaged goods, and Column 3 the micro data for motor vehicles. The sample size in Column 2 is rounded to the nearest 100 to preserve confidentiality.

Table S2: Classification of Subsectors

Goods	Services
Apparel and leather and allied products	Accommodation and food services
Chemical products	Arts, entertainment, and recreation
Computer and electronic products	Construction*
Electrical equipment, appliances, and components	Educational services
	Finance and insurance
Fabricated metal products	Government
Farms	Health care and social assistance
Food and beverage and tobacco products	Information
Forestry, fishing, and related activities*	Other services, except government
Furniture and related products	Professional, scientific, and technical services
Machinery	Real Estate, rental and leasing
Mining, except oil and gas*	Retail trade*
Miscellaneous manufacturing	Transportation and warehousing
Motor vehicles, bodies and trailers, and parts	Utilities
Nonmetallic mineral products	Wholesale trade*
Oil and gas extraction*	
Other transportation equipment	
Paper products	
Petroleum and coal products	
Plastics and rubber products	
Primary metals*	
Printing and related support activities*	
Support activities for mining*	
Textile mills and textile product mills	
Wood products*	

* Subsectors with zero final personal consumption (in the IO table or in the CEX, or both).
Notes: This table lists subsectors within the goods-producing and service sectors according to the detailed 2007 BEA input-output table. Goods-producing services include agriculture, manufacturing, and mining. Subsectors are defined by the 3-digit input-output codes for goods and 2-digit NAICS codes for services (except Management and Administrative Services, which are included in the Professional, Scientific, and Technical Services).

Table S3: List of Motor Vehicle Brands

Brand code	Brand	N	Brand code	Brand	N	Brand code	Brand	N
FOR	Ford	15,566	KIA	KIA	1,551	ISU	Isuzu	250
CHE	Chevrolet	14,576	LEX	Lexus	1,396	SAA	Saab	197
TOY	Toyota	11,972	MEC	Mercury	1,372	POR	Porsche	181
HON	Honda	8,721	BMW	BMW	1,257	MIN	Mini	175
DOD	Dodge	6,417	SAT	Saturn	1,241	LAN	Land Rover	145
NIS	Nissan	5,466	MRB	Mercedes-Benz	1,168	JAG	Jaguar	140
JEE	Jeep	3,177	ACU	Acura	1,145	ZEN	Zenn	96
GMC	GMC	2,771	CAD	Cadillac	1,129	HUM	Hummer	72
CHR	Chrysler	2,489	MIT	Mitsubishi	930	DAW	Daewoo	33
PON	Pontiac	2,318	LIN	Lincoln	796	FIA	Fiat	25
HYU	Hyundai	2,310	VOV	Volvo	709	SMA	Smart	21
BUI	Buick	2,261	INF	Infiniti	566	MGA	MG	16
MAZ	Mazda	1,858	AUD	Audi	444	TES	Tesla	11
VOK	Volkswagen	1,731	SUZ	Suzuki	347	INT	Intl. Harvester	10
SUB	Subaru	1,674	SCI	Scion	314	AUS	Austin-Healey	4

Notes: This table lists 45 brands in the CEX-Ward's sample on motor vehicles (cars and light trucks) and reports the total number of purchases in the CEX.

Table S4: Import Shares by Education Group

	Levels		College minus non-college	
	College, %	Non-college, %	p.p.	% of average
	(1)	(2)	(3)	(4)
A: Industry data, direct + indirect imports (CEX-IO)				
All countries	12.20	12.84	-0.65	-5.13
China	2.00	1.89	+0.11	+5.95
NAFTA	2.50	2.75	-0.25	-9.24
Developed economies	3.06	3.31	-0.25	-7.90
B: Consumer packaged goods, direct + indirect imports (Nielsen-Census)				
All countries	11.50	10.91	+0.59	+5.35
China	4.02	4.20	-0.18	-4.37
NAFTA	1.97	1.88	+0.09	+4.61
Developed economies	3.47	2.93	+0.55	+17.63
C: Motor vehicles, direct imports only (CEX-Ward's)				
All countries	47.73	42.66	+5.08	+11.43
NAFTA	23.07	27.37	-4.30	-16.60
Developed economies	24.66	15.29	+9.37	+50.65

Notes: This table reports the fraction of imports in expenditure for households with and without a college degree, using in turn the CEX-IO sample, the Nielsen-Census sample, and the CEX-Ward's sample. The difference between the import shares of the two education groups are reported in Column 3 in levels, and in Column 4 as a fraction of average import shares.

Table S5: Import Shares by Education Group and Firm Activity: Manufacturing, Wholesale, and Retail (Nielsen-Census Sample)

	Total imports, all products			Imports from China, Health & Household		
	MFG (1)	WH (2)	RT (3)	MFG (4)	WH (5)	RT (6)
All consumers, %	4.37	5.82	0.30	1.98	3.99	0.28
College minus non-college, p.p.	-0.09	0.62	-0.01	-0.11	-0.21	-0.01
$\rightarrow$ Within IO industries	-0.05	0.47	-0.00	-0.10	-0.19	-0.01
N firm-years	12,700	12,700	12,700	3,700	3,700	3,700

Notes: This table estimates the average and differential fraction of imports in spending, decomposed by the main activity of the firm that registered the product: manufacturing (MFG), wholesale (WH), or retail (RT). Other activities are not shown. Each firm is assigned the main activity based on the total payroll of establishments in the corresponding NAICS sectors. Each block of three columns is based on the same data: we decompose import spending into components, without amending the sample.

Table S6: Skill-Bias of Exporters in Census Microdata

	Skill group definition:			
	College graduates	Non-production workers		
	MOPS 2010	CMF 2007	ASM 2010	MOPS 2010
	(1)	(2)	(3)	(4)
Average export share, %	22.84	14.70	19.47	22.84
Differential export share, skilled minus unskilled, p.p.:				
Overall	+5.26	+4.50	+4.52	+5.36
→ Between industries	+4.49	+4.09	+4.51	+5.20
→ Within industries	+0.77	+0.41	+0.01	+0.16
N establishments	33,400	294,200	50,500	33,400

Notes: This table shows the payroll-weighted average export shares (exports as % of sales) for three samples of manufacturing establishments: the 2010 MOPS (Columns 1 and 4), the 2007 Census of Manufactures (Column 2) and the 2010 Annual Survey of Manufactures (Column 3); see Appendix S.2.8 for data description. The table also shows the differential exposure for skilled and unskilled workers and decomposes it into "between" and "within" components across six-digit NAICS industries. Skilled workers are defined as college graduates in column 1 and non-production workers in the other columns.

Table S7: Summary Statistics, Nielsen-Census Sample

	All products	By Product Class		
		Food	Health & Household	General Merchandize
Spending share of imports, %	11.10	6.92	14.58	27.96
→ Imports from China	4.15	0.88	6.51	17.91
→ Imports from NAFTA	1.91	1.67	2.19	2.74
→ Imports from Developed Economies	3.10	2.42	4.24	4.90
% of Product Class in Total Sales	100.00	67.29	20.24	12.48
N firms	8,200	5,700	2,400	2,000
N firm-years	12,700	9,000	3,700	2,800
N firm-module-years	131,000	88,600	29,800	12,500

Notes: This table reports statistics on imports based on the merged Nielsen-Census sample, within consumer packaged goods overall and for three product classes: Food, Alcohol, and Tobacco ("Food"), Health and Beauty Products and Household Supplies ("Health and household"), and General Merchandize. Imports are measured at the firm level and the summary statistics are computed using the square-root of firms' Nielsen sales as weights. The reported percentage of each product class uses the same weighting scheme. The numbers of observations are rounded to the nearest 100 to preserve confidentiality.

Table S8: Nielsen-Census Matching Rules

	Non-missing exact match	Exact and [fuzzy] match
Rule 1	Zip-9	House, Name, Address, PO Box, Unit, Bldg
Rule 2		House; [Name, Address, PO Box, Unit, Bldg]
Rule 3	Zip-5, House	Name, Address, PO Box, Unit, Bldg
Rule 4		[Name, Address, PO Box, Unit, Bldg]
Rule 5	Zip-5	Name
Rule 6	City	Name, State
Rule 7	State	Name, Entity

Notes: This table lists the rules used to match names and addresses in the Nielsen and Census samples. Each rule requires an exact match and non-missing values of the variables listed in the first column, as well as an exact or probabilistic (fuzzy) match on the variables from the second columns (missing values are allowed). Variables where fuzzy match is allowed are listed in brackets. For fuzzy matching, a 75% threshold is chosen for the match quality score assigned by the `reclink2` package from Wasi and Flaaen (2015).

Table S9: Nielsen-Census Match Statistics

A: Nielsen firms

	2007		2012	
	Firms	% of Sales	Firms	% of Sales
All Nielsen	26,900	100.00	28,600	100.00
Nielsen with size filter	11,000	99.77	12,100	99.82
Matched to SSEL, same year	7,600	83.19	8,900	87.29
Matched to SSEL, any year	8,200	90.76	9,300	91.86
Matched to Economic Census	7,200	88.68	7,800	88.57
Passed consistency filter	6,100	83.02	6,600	83.61

B: Census firms in Food, Alcohol, and Tobacco

	All years	
	Firms	% of Sales
All Census	51,500	100.00
Matched to Nielsen	8,900	78.96
Matched to Nielsen with size filter	5,200	75.57
Passed consistency filter	4,800	58.73

Notes: This table reports the number of firms and the percentage of total sales remaining after each step of the merging process between the Nielsen and Census samples, explained in detail in Appendix S.2.2. Panel A measures these statistics relative to the full Nielsen sample (for 2007 and 2012 Economic Censuses separately), while Panel B measures them relatively to the set of Census firms active in the Food, Alcohol, and Tobacco Manufacturing industries (NAICS codes 311 and 312). The last line of each panel corresponds to the final merged sample, for all firms in Panel A and for those in food, alcohol, and tobacco in Panel B. The numbers of firms are rounded to the nearest 100 to preserve confidentiality.

Table S10: Distribution of Match Types, Nielsen-Census Sample

	% of Matched Firms (1)	% of Sales (2)	% of $\sqrt{}$ Sales (3)
Multi-establishment firms			
Rule 1	10.30	19.72	17.88
Rule 2	4.12	18.99	10.76
Rule 3	5.21	19.86	12.77
Rule 4	3.87	18.54	9.82
Rule 5	2.54	4.12	4.46
Rule 6	1.72	6.80	4.75
Rule 7	1.65	5.11	4.34
Total multi-establishment	29.42	93.14	64.79
Single-Establishment Firms			
Rule 1	33.87	3.42	17.23
Rule 2	10.27	0.87	4.87
Rules 3–7	26.44	2.57	13.12
Total single-establishment	70.58	6.86	35.21

Notes: This table shows the fractions of the Nielsen-Census merged sample corresponding to each of the merging rules, described in Data Appendix S.2.2. Column 1 shows the raw fraction of Nielsen firms in each category, while Column 2 shows the share of total Nielsen sales, and Column 3 weights firms by the square-root of Nielsen sales.

Table S11: Distribution of NAICS Industries, Nielsen-Census Sample

NAICS Industry		% of Firms	% of Sales	% of $\sqrt{\text{Sales}}$	% of Private Label Brands
Code	Description	(1)	(2)	(3)	(4)
	2-digit NAICS codes				
31-33	Manufacturing	49.78	61.63	57.17	1.21
42	Wholesale	39.37	16.02	29.00	7.90
44-45	Retail	4.80	18.55	8.66	93.74
—	Other	6.04	3.80	5.18	5.19
	3-digit NAICS codes				
311	Food Manufacturing	31.16	36.74	34.78	0.73
312	Beverage and Tobacco Manufacturing	5.73	6.68	6.26	0.30
322	Paper Manufacturing	0.75	4.76	1.96	1.86
325	Chemical Manufacturing	5.36	8.18	6.97	2.79
423	Durable Goods Wholesalers	8.34	2.20	5.86	5.91
424	Nondurable Goods Wholesalers	29.96	15.24	23.05	6.49
445	Food and Beverage Stores	2.24	9.82	4.97	99.10
—	Other	16.44	16.38	16.16	49.69

Notes: Columns 1–3 of this table report the fractions of the Nielsen-Census merged sample corresponding to selected 2- and 3-digit NAICS sectors. Each firm in the Economic Census is classified into the sector where its establishments have the highest total payroll. Column 1 shows the raw fraction of firms in each sector, while Column 2 shows the share of total Nielsen sales, and Column 3 weights firms by the square-root of Nielsen sales. Column 4 measures, for firms in each sector, the sales share of Nielsen barcodes that are classified as private label brands—brands that belong to the retail store. We identify them in the Nielsen data as those which contain "CTL BR" in the barcode description.

Table S12: Nielsen-Census Sample Selection

A: Nielsen Firms

	N	% of Total Sales	Median Sales, $k	% of Sales to College Grads	Mean HH Income, $k
Matched	12,700	83.50	1,904	29.14	67.63
Didn't Match	10,400	16.50	981	30.71	69.75
P-value of t-test				[0.009]	[0.008]
P-value controlling for size				[0.425]	[0.028]

B: Census Firms in Food, Alcohol, and Tobacco

	N	% of Sales	Median Sales, $k	Median Payroll, $k	Median Employment	Mean Skill Intensity
Matched	4,800	58.73	13,303	1,889	54	0.336
Didn't Match	46,600	41.27	606	113	4	0.341
P-value of t-test						[0.744]

Notes: This table compares firms in the matched Nielsen-Census sample to other firms in Nielsen (Panel A) and in the Economic Census (Panel B) which did not find a match, in terms of size, consumer, and producer characteristics. The universe of firms in Panel A is all Nielsen firms that passed the size filter, while in Panel B it is all firms in the Economic Census active in Food, Alcohol, and Tobacco Manufacturing. P-values for t-tests for equality of means between the matched and unmatched samples are shown in brackets. The last row of Panel A performs such t-test controlling for a quadratic polynomial in log firm sales. The numbers of firms are rounded to the nearest 100 and medians are computed as geometric means of the 45 and 55 percentiles to protect confidentiality.