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THE DISTRIBUTIONAL EFFECTS OF TRADE: THEORY AND EVIDENCE FROM THE UNITED STATES

Kirill Borusyak
Xavier Jaravel

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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.

Kirill Borusyak
University College London
Drayton House
30 Gordon Street
London
WC1H 0AX
United Kingdom
k.borusyak@ucl.ac.uk

Xavier Jaravel
London School of Economics
Houghton Street
London
WC2A 2AE
United Kingdom
x.jaravel@lse.ac.uk

An online appendix is available at http://www.nber.org/data-appendix/w28957

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

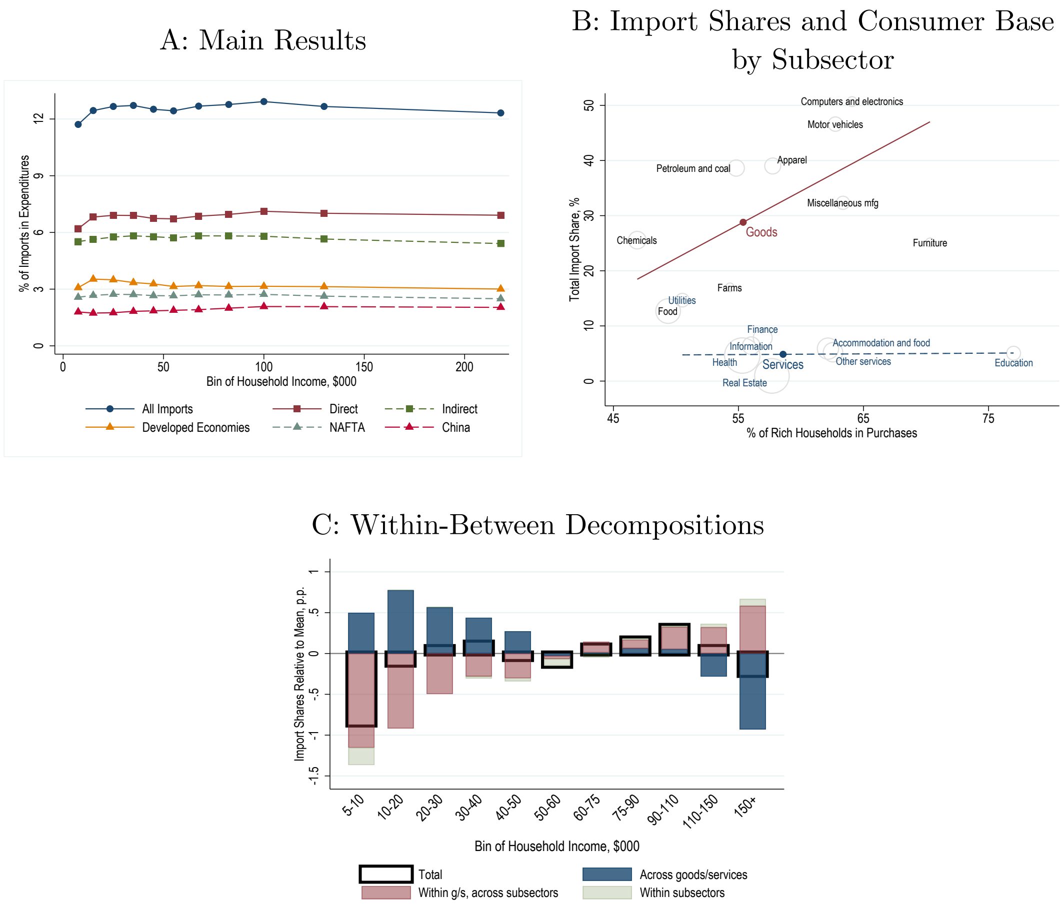
Panel A of Figure 1 reports the import shares of expenditures across the income distribution, for overall imports and for several decompositions, using industry-level data from the CEX linked to the IO table. It shows little variation in the total import share around the national average of 12.6%. For 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.

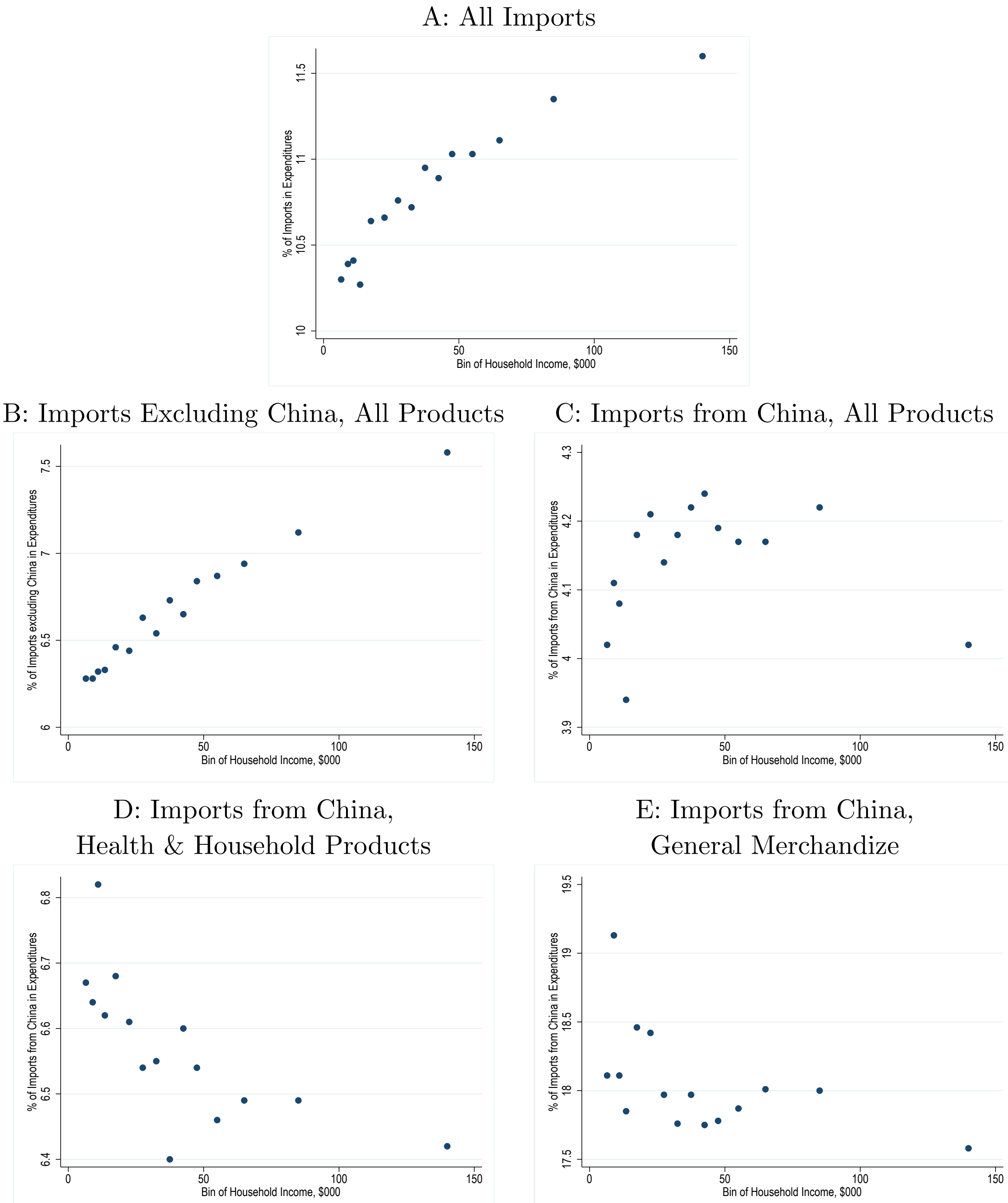
3.2 Import Shares within Consumer Packaged Goods

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



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]

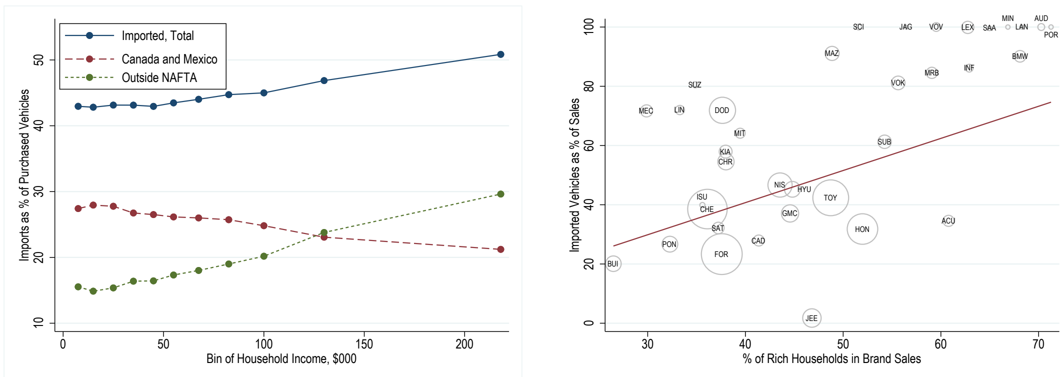
Overall, we find that higher-income households buy more imports, in particular from countries other than China, consistent with differences in product quality. But the differences in import shares are relatively small, confirming the finding of a distributionally neutral expenditure channel.

[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?

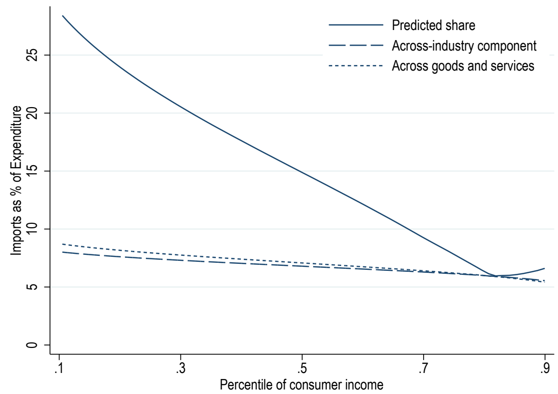
To understand the source of the discrepancy with our results, it is instructive to first examine the import spending shares inferred by the AIDS demand system with the parameters estimated by FK. In their model, like in our Section 2.1, import shares are directly informative about the effects of small 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

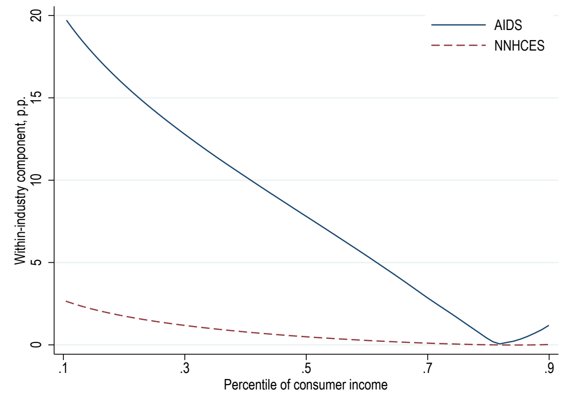
[21] We have verified that our first-order approximation is accurate for measuring the gains from a 5% reduction in foreign tariffs, reported in Section V.E of FK.

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

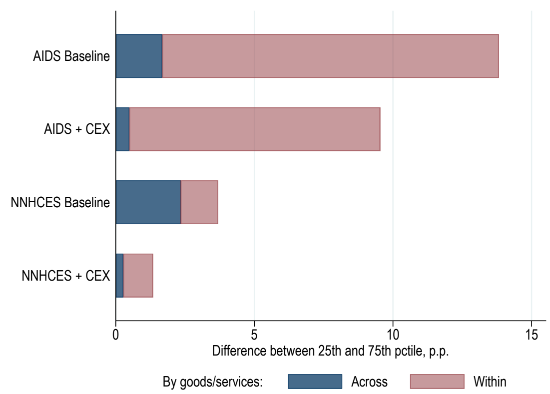
A: Imports Shares across Income Groups: AIDS Estimated by Fajgelbaum and Khandelwal (2016)



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.

$\widetilde{IP}^{\text{Int}}_{jc}$, 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*

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

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

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

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

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 $\widetilde{IP}^{\text{Int}}_{jc}$ in production costs.

The final terms are the *income and substitution effects.* Partial equilibrium welfare gains, driven by the import share $ImpSh^x_c$, 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)).

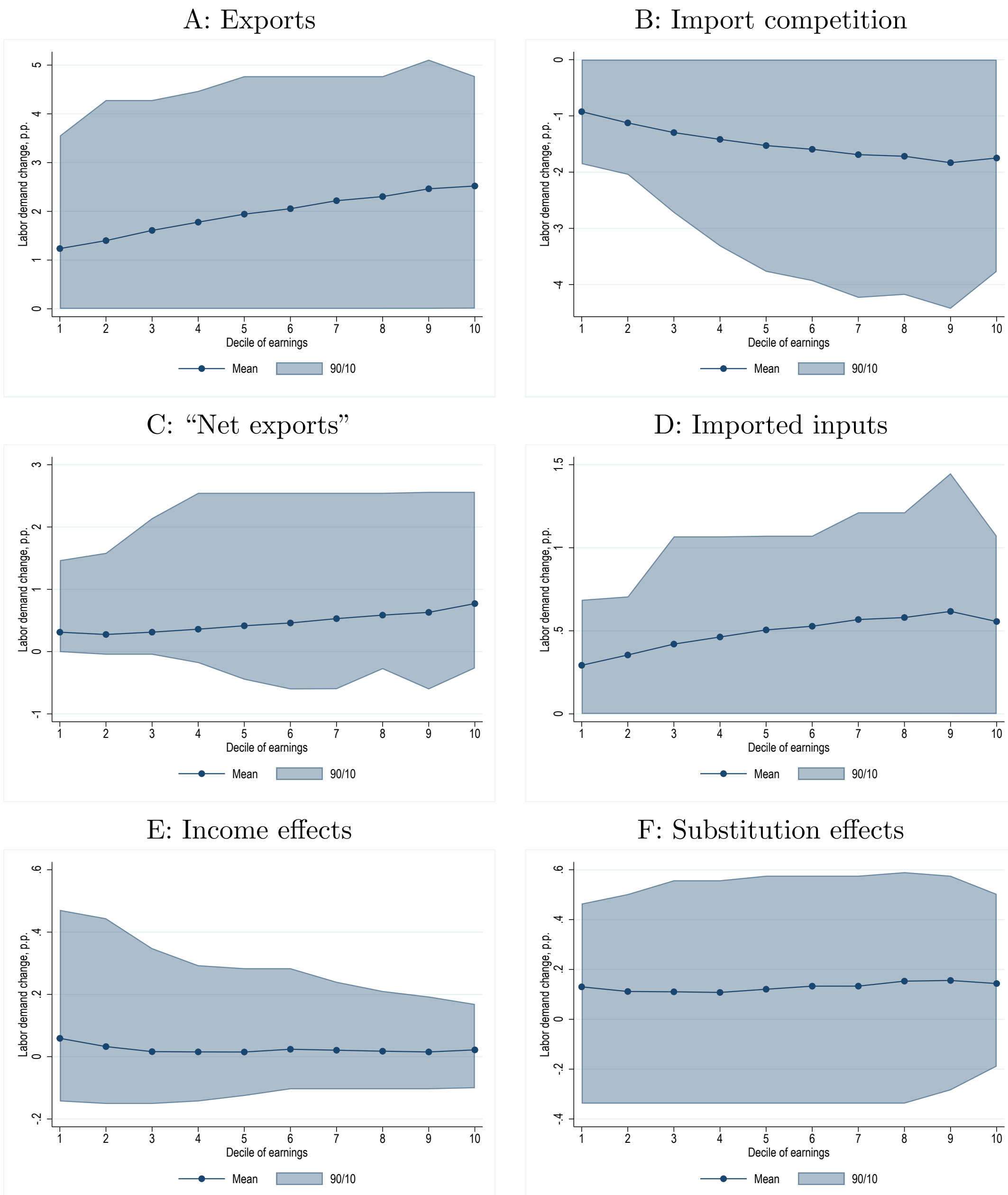
Proposition 2 finally requires us to calibrate the $\tilde{\boldsymbol{G}}$ matrix. While in general it may depend on the patterns of local labor substitution in each industry (through the F_j^{VA} functions), Appendix C.2 shows how it simplifies in the two calibrations we consider. Specifically, absent 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

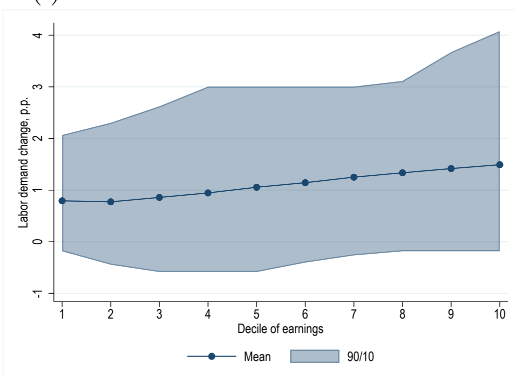
[36]The fraction of losers varies non-monotonically with income. While Panel A of Figure S9 reports the overall fraction of losers, Panel B shows that they are found especially within goods-producing industries, in which some industries suffer from import competition.

[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.

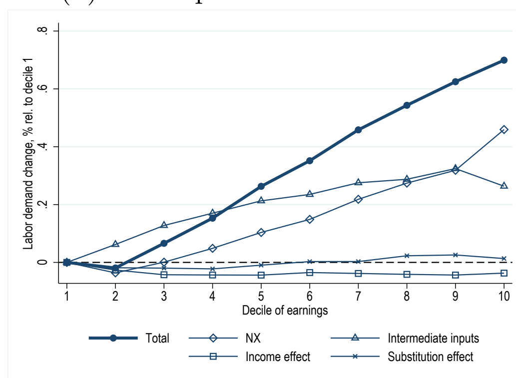
Figure 6: Worker-Level Welfare Effects of a 10% Fall in Trade Costs by Income Decile

A: Partial equilibrium labor demand response

(i) Across and within income deciles

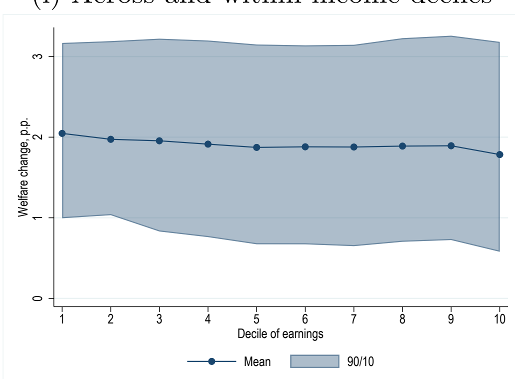


(ii) Decomposition into channels

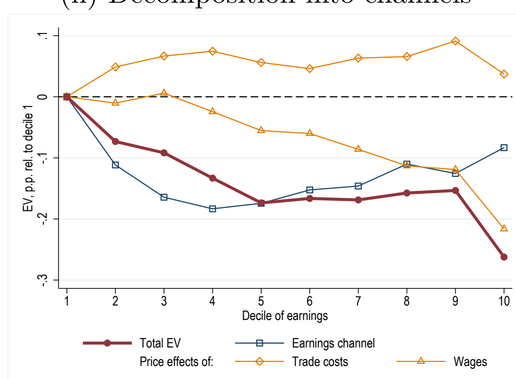


B: General equilibrium welfare response

(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. $\text{SD}\left(\log X + \log \mathcal{W}\right) - \text{SD}\left(\log X\right)$. 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.

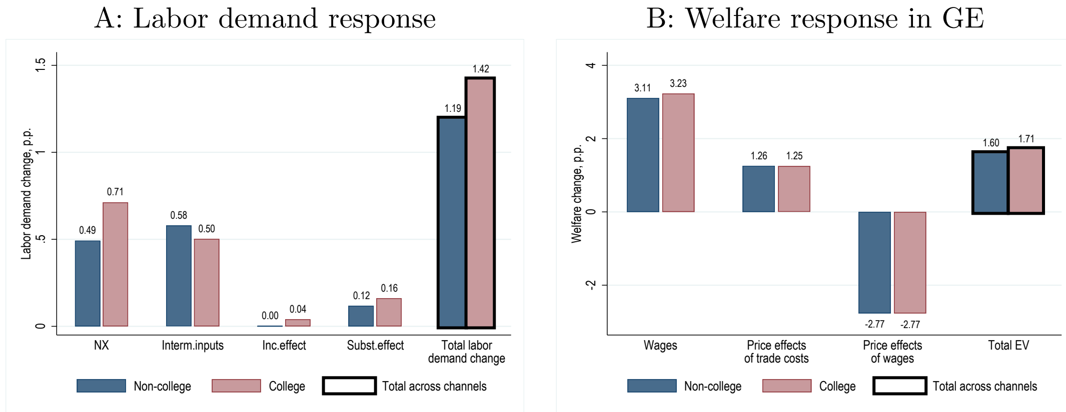
5.4 Distributional Effects across Education Groups

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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