

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

Kirill Borusyak
Princeton University

Xavier Jaravel
London School of Economics

October 6, 2018

Abstract

We quantify the distributional effects of trade shocks in the U.S. through consumer prices (*expenditure channel*) and wages (*earnings channel*). A quantitative trade model links these channels to compositional differences in expenditures and earnings across household groups. New data reveal that spending shares on imports are similar across education and income groups, implying a neutral expenditure channel. Estimated differences in workers' exposure to import competition, exporting, and income effects indicate that the earnings channel favors college graduates. Overall, a uniform trade cost reduction generates welfare gains that are 25% larger for college graduates. Similar results apply to trade with China.

Keywords: Trade liberalization, Inequality, Non-homothetic preferences, Skill premium

JEL Codes: F14, F16, F60, D63

*Borusyak: borusyak@princeton.edu; Jaravel: x.jaravel@lse.ac.uk.

We are particularly indebted to Pol Antràs, Cecilia Fieler, Teresa Fort, Edward Glaeser, Gita Gopinath, Alonso de Gortari, Elhanan Helpman, Oleg Itskhoki, Lawrence Katz, Danial Lashkari, Marc Melitz, Tom Sampson, Felix Tintelnot, and Oren Ziv for insightful comments. We are also grateful to numerous seminar and conference participants for thoughtful suggestions. We thank Jim Davis for his help at the Boston Census Research Data Center and James O'Brien for sharing a concordance between CEX categories and NAICS industries with us. The research in this paper was conducted while Borusyak was a Special Sworn Status researcher of the U.S. Census Bureau at the Boston Census Research Data Center. Any opinions and conclusions expressed herein are those of the authors and do not necessarily reflect the views of the U.S. Census Bureau. All results have been reviewed to ensure that no confidential information is disclosed. Researchers own analyses calculated based in part on data from The Nielsen Company (US), LLC and marketing databases provided through the Nielsen Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the Nielsen data are those of the researchers and do not reflect the views of Nielsen. Nielsen is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

1 Introduction

Are the gains from trade, and the losses from protectionism, unequally distributed in society? Despite extensive research, the answer to this question remains debated. In the United States, policymakers on both sides of the aisle have recently proposed increasing import tariffs with major trading partners amid growing concerns over the impact of trade on inequality. Both canonical and more recent trade theories predict that trade should negatively impact the earnings of low-skilled workers in the U.S. (e.g., [Stolper and Samuelson \(1941\)](#), [Burstein and Vogel \(2017\)](#), [Caron et al. \(2017\)](#), and [Cravino and Sotelo \(2018\)](#)). However, an emerging line of research suggests that the benefits of trade due to falling consumer prices may disproportionately accrue to low-income households ([Fajgelbaum and Khandelwal 2016](#)). The net effect on inequality is therefore ambiguous.

This paper provides new evidence on the distributional effects of trade through both consumer prices (expenditure channel) and wages (earnings channel), 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; they include expenditure microdata on consumer packaged goods and motor vehicles merged with restricted access customs data. To preserve tractability of the labor market analysis, we focus on the effects on two skill groups, with and without a college degree, and take a comparative static approach that abstracts from transition dynamics. We find that the expenditure channel is distributionally neutral, while the earnings channel moderately favors college graduates.

A set of intuitive reduced-form statistics—moments of the data that capture the differential exposure of skill groups to trade—plays a central role in our analysis. The key statistic governing the expenditure channel is the difference in spending shares on imports, both directly via purchases of imported products and indirectly via imported intermediate inputs. The group that spends relatively more on imports enjoys larger purchasing-power benefits from trade liberalizations. The earnings channel in turn stems from differences in workers’ exposure to trade, as measured by import penetration, export shares, usage of imported intermediate inputs, and income elasticities for different industries.

These statistics emerge from a quantitative trade model. We build this model with three goals: to guide the reduced-form measurement, to perform the counterfactual analysis of trade policies, and to isolate the contributions of different mechanisms to the distributional effects. The counterfactuals necessarily depend on the model’s assumptions, which we discuss in detail below.

The first part of the paper compares spending on imports between skill groups. We first use the Consumer Expenditure Survey (CEX) as a source of expenditures on all goods and services by group. We match spending categories in the CEX to detailed industries in the Bureau of Economic Analysis input-output table for 2007 to measure the import content (i.e., the fraction of imports in value) of each industry, accounting for trade in intermediate goods and in services. We then exploit expenditure microdata available at a much finer firm level for two large classes of goods. For consumer packaged goods, we match barcoded products from the Nielsen Homescan Consumer Panel to their manufacturers or distributors in the confidential U.S. Economic Census and Customs microdata. We proxy for a product’s

import content with the ratio of imports to total sales of the corresponding firm.¹ We also link brands of cars and SUVs from the CEX questionnaire on vehicle purchases to Ward’s Automotive statistics on U.S. vehicle imports, as well as to the Census of Manufactures and Customs data to account for imported vehicle parts. Consumer packaged goods and motor vehicles together cover around 40% of total expenditures on goods.

Our key finding is that the expenditure channel is distributionally neutral due to offsetting forces. On the one hand, college graduates consume a larger share of services, which are largely non-traded. On the other hand, spending of college graduates on goods is skewed toward industries with higher import penetration rates, such as electronics (e.g., relative to food). Moreover, within consumer packaged goods and motor vehicles, college graduates spend relatively more on imported brands, particularly those that come from developed countries and are more expensive. These forces largely compensate each other, resulting in similar overall spending shares on imports across education groups, around 12.6%. The patterns are similar when we compare import spending across income groups.

Our results stand in contrast with [Fajgelbaum and Khandelwal \(2016\)](#), who infer consumption baskets of different groups based on aggregate international trade flows and a structural model. While their model has attractive aggregation properties and can be estimated without detailed data, it predicts substantially larger import spending by low-income groups, which we do not find in U.S. data.²

We also document differences in spending on imports from specific countries of origin, in particular from China. Consistent with our prior, Chinese brands of consumer packaged goods are less expensive and tend to be purchased more often by less educated and poorer households. However, imports from China are concentrated in industries with higher expenditure shares for more educated and richer households (e.g., electronics), which provides an offsetting force. Overall, spending shares on imports from China are similar across education and income groups, around 2%.

The second part of the paper presents the reduced-form patterns governing the earnings channel. We find that college graduates work in industries that (a) are less exposed to import competition (overall and from China), (b) export more, (c) sell more income-elastic products, and (d) have a lower share of imported intermediate inputs.³ Viewed through the lens of our model, a trade liberalization increases the college wage premium through the first three forces and decreases it through the fourth. Indeed, import-competing industries shrink due to trade, which reduces labor demand for the skill group they are intensive in. Furthermore, trade induces an expansion of industries which export, are income-elastic, or use imported inputs; these industry expansions affect relative labor demand accordingly.

The third part of the paper performs counterfactual analyses, based on a model similar to [Caron](#)

¹With this strategy, we capture imports of both final products and intermediate inputs. A potential limitation is that the bridge is constructed at the firm level (by firm name and address), so barcodes produced by a multi-product firm are assigned the same import intensity, potentially leading to an aggregation bias. However, we provide an upper bound for this bias and find that the bias is small (see Section 4 for a complete discussion).

²Their estimates imply that the spending share on imports is around 8 *percentage points* higher for consumers at the 75th percentile of income distribution relative to the 25th percentile, on average across countries (Figure XII). While they do not report comparable figures for the U.S., those are likely to be as strong, based on the large pro-poor gains relative to autarky reported in Table V of their paper.

³These results use industry-level data. We address potential aggregation biases where possible (see Section 6.3).

et al. (2017), Cravino and Sotelo (2018), and Morrow and Treffer (2017). The home economy is small and populated by skilled and unskilled agents. Their preferences over composite goods of different industries belong to a flexible class that combines non-homotheticities as in Comin et al. (2016) with a nested CES structure. Agents inelastically supply a unit of labor and are freely mobile across industries. Industries, which include goods and services, supply varieties that are differentiated by country of origin, generating a standard gravity equation. Markets for each variety are perfectly competitive, and production technologies exhibit constant returns to scale. Trade flows in the model are shaped by product differentiation and arbitrary differences in technology and skill endowments. We perturb the equilibrium observed in the data with a counterfactual trade shock and characterize the impact on prices and wages in comparative statics using a first-order log-linear approximation.

Our model is stylized in certain dimensions but has the virtue of tractability: general equilibrium counterfactuals can be computed based on the reduced-form statistics documented in the previous parts of the analysis.⁴ The small open economy assumption implies that trade policy shocks do not affect foreign factor prices; hence U.S. data are sufficient for the analysis. The assumption of perfect competition in turn generates complete pass-through of trade costs into prices, which implies that differences in spending shares on imports govern the expenditure channel in the log-linear approximation. On the earnings side, the class of preferences we employ simultaneously allows for rich but tractable income and substitution effects. Finally, free mobility of workers conveniently reduces inequality to a single dimension: education (skill). Mobility costs are known to be important for the transitory effects of trade (e.g., Artuç et al. 2010, Autor et al. 2014, and Traiberman 2018), but should play a smaller role in the long-run. Moreover, under standard assumptions, mobility costs only add exogenous within-group inequality which remains unaffected by trade shocks.

Using the model, we show that the distributional effects of trade moderately favor college graduates, primarily through the earnings channel. A 10% reduction in trade barriers with all trading partners of the U.S. generates welfare gains that are positive for both groups but 25% higher for college graduates (1.90% vs. 1.52%, measured as a fraction of consumption).⁵ Three main forces contribute similar amounts to the earnings channel: differences in import penetration, differences in income elasticities, and substitution effects stemming from the complementarity between goods and services. Imported intermediate inputs mildly weaken the earnings channel, while general equilibrium forces and differences in export shares slightly strengthen it. Moreover, we find that the expenditure channel does not offset the earnings channel: it is in fact slightly biased in favor of college graduates. We also consider a 10% reduction in prices of imports specifically from China and find qualitatively similar effects.

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 infer differences in

⁴In addition, we need trade elasticities and elasticities of substitution across the product space on the demand side, as well as the aggregate elasticity of substitution between workers with and without a college degree on the supply side. We use typical values estimated in the literature and verify robustness to a range of other values.

⁵The shock we consider can be interpreted as a 10 percentage point reduction in ad valorem tariffs, ignoring the extra tariff revenue, or as a reduction in transportation costs which makes imported and exported goods 10% cheaper.

import spending across groups from aggregate trade flows: [Fajgelbaum and Khandelwal \(2016\)](#) and [He \(2018\)](#) 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. A small number of papers directly measure spending on imports and compare them across consumer groups: [Porto \(2006\)](#) for Argentina, [Faber \(2014\)](#) for Mexico, [Levell et al. \(2017\)](#), [Dhingra et al. \(2017\)](#), and [Breinlich et al. \(2017\)](#) for the U.K., and [Hottman and Monarch \(2018\)](#) for the U.S. Data limitations force these papers to focus only on particular types of differential spending.⁶ In contrast, our paper considers the entire economy, taking into account imports of both final and intermediate goods, and at the same time uses very detailed data on consumer packaged goods and motor vehicles to address potential aggregation biases. Lastly, we focus on counterfactual shocks, while a related literature evaluates the effects of historical trade shocks on U.S. prices: [Amiti et al. \(2018a\)](#) and [Jaravel and Sager \(2018\)](#) quantify the reduction of U.S. prices due to trade with China; [Bai and Stumpner \(2018\)](#) 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 \(2018\)](#) show that lower-income households experienced larger growth of import prices between 1998 and 2014.

The relationship between our work and the extensive literature on the distributional effects of trade through the earnings channel is threefold. First, the modeling framework allows us to assess the relative importance of several key mechanisms that were previously studied separately, namely: the role of skill endowment emphasized by the Stolper-Samuelson theorem, the contributions of non-homothetic preferences ([Caron et al. 2017](#)), the complementarity between goods and services ([Cravino and Sotelo 2018](#)), and the skill bias of exporters ([Burstein and Vogel 2017](#)). Second, our focus on reduced-form statistics echoes the literature that highlighted the role of the skill content of trade (e.g. [Borjas et al. 1997](#); [Krugman 2000](#)). Our model departs from Hecksher-Ohlin, and thus the relevant statistics are also different. Finally, our findings are consistent with the existing empirical literature suggesting that globalization was not an important driver of the rising skill premium in the U.S. in the 1980s (e.g., [Lawrence and Slaughter 1993](#), [Berman et al. 1994](#), [Borjas et al. 1997](#), [Krugman 2000](#)). While our counterfactuals are not directly comparable, we also find that inequality does not respond strongly to trade shocks and explain this result by the similar exposure of skill groups to trade.⁷

⁶[Porto \(2006\)](#) captures differences in spending across seven large categories of final goods and services, [Faber \(2014\)](#) looks at imported intermediate inputs, [Levell et al. \(2017\)](#) limit their analysis to 9 categories of food, and [Dhingra et al. \(2017\)](#) and [Breinlich et al. \(2017\)](#) consider 12–13 broad groups of goods and services consumed by households. In contemporaneous work, [Hottman and Monarch \(2018\)](#) 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 related papers, [Furman et al. \(2017\)](#) and [Gailles 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. Finally, [Cravino and Levchenko \(2017\)](#) measure the differences in inflation across income groups in Mexico following a currency devaluation which raised import prices. They capture both across- and within-industry patterns but, due to data limitations, rely on strong assumptions to estimate the latter.

⁷Note that in more recent work, [Autor et al. \(2013\)](#) and [Acemoglu et al. \(2016b\)](#) find negative effects of trade with China on manufacturing employment in the U.S. at the level of commuting zones and industries, respectively, which is consistent with our calibration. However, they remain largely silent about the effect of trade on inequality: they do not find significantly

Finally, this paper contributes to an emerging literature that analyzes the expenditure and earnings channels jointly, in a unified framework. To the best of our knowledge, 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 \(2018\)](#) generalizes the structural model of [Fajgelbaum and Khandelwal \(2016\)](#). As previously discussed, we take a different approach by focusing on a set of reduced-form statistics measured in detailed data.

The remainder of the paper is organized as follows. Section 2 presents the model. Sections 3–5 report estimates of spending on imports: Section 3 focuses on patterns across industries covering the entire U.S. economy, Section 4 provides complementary estimates using scanner data for consumer packaged goods, and Section 5 presents the patterns using detailed expenditure data on vehicles. Section 6 reports the reduced-form patterns on import competition, exports, income elasticities and the use of imported intermediate inputs, which together govern the earnings channel. Finally, Section 7 presents the estimates of the distributional effects from counterfactual trade policies, feeding the reduced-form patterns from the previous sections through the model. Section 8 concludes.

2 Theory

We develop a model to characterize the welfare consequences of counterfactual changes in trade costs across skill groups. This section first presents the model in a special case without input-output linkages and then describes the full model used for counterfactual analyses. Online Theory Appendix A provides the proofs. To facilitate reading, online Appendix Table A1 provides a catalog of the variables we use.

2.1 Setup

Trade, Preferences, and Technologies. We study a static global economy with $\mathcal{C} + 1$ countries in which international trade is shaped by product differentiation, cross-country differences in technologies and endowments, and trade costs. The United States is denoted $c = H$ (Home) and the set of all other countries F (Foreign). The home economy is assumed to be sufficiently small, such that shocks to trade costs between Home and any other countries do not affect foreign prices for goods and factors.⁸

The home economy is populated by two types of agents: skilled ($i = S$) and unskilled ($i = U$), with measures L_i . They derive utility $\mathcal{U}(Q_1^i, \dots, Q_{\mathcal{J}}^i)$ from consuming composite products of \mathcal{J} industries, which include both goods and services. They spend $X_j^i = p_j Q_j^i$ on products from industry j , which constitutes a share $s_j^i = X_j^i / X_i$ of their total spending $X_i = \sum_j X_j^i$. Throughout the paper, we use superscripts (subscripts) to denote buyers (sellers); agents are buyers in the product markets and sellers

different cross-sectional effects on skilled and unskilled wages (Tables 6 and 7 in [Autor et al. 2013](#)) and do not document the distribution of trade shocks across commuting zones.

⁸While the U.S. accounts for a substantial fraction of world GDP, it is not as large a trading partner for the rest of the world. According to the World Development Indicators database, exports from the U.S. constitute only 3.9% of absorption in other countries; exports to the U.S. account for only 5.5% of foreign production. Both patterns predict that the impact of U.S. trade shocks via changing foreign prices on the U.S. economy should be limited.

in the labor market. Agents all inelastically supply one unit of labor. We assume that labor is freely mobile across industries (but immobile across countries), implying that domestic wages w_i differ only across skill levels, not within. Prices and wages are measured relative to a foreign numeraire. We allow the budget to be imbalanced to account for the large trade deficit in the U.S., assuming that the total expenditure of each agent is a multiple of her wage, $X_i = \zeta_i w_i$, with an exogenous constant ζ_i .⁹

To model domestic preferences, we use a flexible demand system that embeds non-homothetic CES preferences from [Hanoch \(1975\)](#) in a two-tier nesting structure. This demand system captures complementarity between goods and services (the upper tier) and substitution between industries within each of the two sectors (the lower tier). It inherits the desirable property of non-homothetic CES that income and price elasticities are shaped by independent parameters (see [Comin et al. 2016](#) and [Matsuyama 2017](#)). These features of the demand system allow us to jointly accommodate and compare the distributional impacts of several types of demand responses to trade shocks that were previously examined in isolation (e.g., [Caron et al. 2017](#) and [Cravino and Sotelo 2018](#)). Non-homothetic nested CES utility is defined recursively by

$$\begin{aligned} \mathcal{U}_i &= \left(\sum_r (Q_r^i)^{(\rho-1)/\rho} \right)^{\rho/(\rho-1)}, \quad r = \text{Goods, Services} \\ Q_r^i &= \left(\sum_{j \in r} (a_j \mathcal{U}_i^{\varphi_j - 1})^{1/\varepsilon_r} (Q_j^i)^{(\varepsilon_r - 1)/\varepsilon_r} \right)^{\varepsilon_r/(\varepsilon_r - 1)}, \end{aligned} \quad (1)$$

where the Q_r^i are sectoral aggregates of consumption, a_j are taste shifters, and ρ and ε_r are elasticities of substitution between and within sectors, respectively. Primitive parameters φ_j map into income elasticities, which we denote by ψ_j , according to equation (A9) in the online Appendix.

Each industry j consists of a set of differentiated varieties sold in perfectly competitive markets. The structure of product differentiation we impose gives rise to a standard industry gravity equation. For brevity of notation, we use the [Armington \(1969\)](#) formulation of the product space: there is one variety per country and industry, and varieties are combined with constant elasticity of substitution ξ_j , so that $Q_j^i = \left(\sum_c b_{jc}^{1/\xi_j} (Q_{jc}^i)^{(\xi_j - 1)/\xi_j} \right)^{\xi_j/(\xi_j - 1)}$, where b_{jc} are taste shifters.¹⁰ Accordingly, the industry price index is $p_j = \left(\sum_c b_{jc} p_{jc}^{1 - \xi_j} \right)^{1/(1 - \xi_j)}$, where prices p_{jc} are inclusive of iceberg trade costs τ_{jc} for imported products. The microfoundation from [Eaton and Kortum \(2002\)](#) is isomorphic to this setup (the Fréchet parameter plays the role of the trade elasticity $\xi_j - 1$). The results are also unchanged if there is more than one variety per country and industry but there is no entry or exit.

Domestic production combines labor inputs, and there are no other factors of production (until we

⁹The U.S. has run a trade deficit every year since 1976, with imports exceeding exports by 48% in 2007. Although the ratio of net imports to GDP (the average of $\zeta_i - 1$ across types in the model) fluctuates over time (see Online Appendix Figure A1), our assumption provides a better fit to the data than balanced trade. It is more common to assume that the absolute value of net imports is fixed ([Dekle et al. 2008](#)), but our approach is more tractable in a model with multiple agent types, as we do not need to keep track of income and expenditure changes separately.

¹⁰This aggregator is homothetic, so there are no differences in spending patterns across consumers within an industry. We return to this issue in Section 2.4.

introduce materials in Section 2.3). Output is given by $Q_{jH} = F_{jH}(L_S^j, L_U^j)$, where F_{jH} is some constant returns to scale function and L_i^j is type- i labor employed in j . The equilibrium share of group i 's earnings originating from industry j is denoted $e_i^j = w_i L_i^j / w_i L_i$. We remain agnostic about foreign endowments, preferences, and technologies, requiring only that foreign buyers aggregate varieties across countries of origin with the same elasticity ξ_j as domestic buyers. Since Home is small and does not affect industry price indices abroad, there are no income or substitution effects at the industry level abroad, and the export demand elasticity for domestic products is also ξ_j . Therefore, the quantity of exports satisfies $Q_{jH}^{\text{Export}} = a_j^{\text{Export}} (p_{jH} \tau_j^*)^{-\xi_j}$, where τ_j^* is the exporting iceberg trade cost and a_j^{Export} are constants.

Counterfactuals. The equilibrium is defined by (i) utility-maximizing allocation of spending across industries by domestic consumers of each skill type and foreign consumers, (ii) zero profit conditions for domestic and foreign producers, and (iii) labor and product market clearing conditions (see Theory Appendix A.1 for details). To characterize how the equilibrium responds to counterfactual trade shocks, we rely on a first-order log-linear approximation around the equilibrium, which is precise when the trade shocks are small. Formally, we use the “hat algebra” of Jones (1965) letting hats denote relative changes from the original equilibrium (e.g., \hat{p}_j and \hat{w}_i for changes in consumer prices and wages).

The distributional effects of a change in trade policy depend on the set of industries and of trading partners that are affected by the policy change. With trade policies skewed towards specific industries or trading partners, one could plausibly generate any result. To discipline the analysis, we consider two main policies that are uniform across industries: (i) a bilateral reduction of tariffs with all foreign countries, and (ii) a unilateral reduction of tariffs on Chinese imports.¹¹ The first policy reduces consumer prices for all imported goods at home and exported goods abroad, so we interpret its effects as the overall distributional effects of international trade. The second policy is motivated by the large increase in imports from China in recent years and by the evidence for its sizable employment effects (Autor et al. 2013; Autor et al. 2014; Caliendo et al. 2018; Pierce and Schott 2016). These policies can be thought of as changes in tariffs, but reductions of iceberg transportation costs or of other value-based barriers are isomorphic.¹² We parameterize each policy as by a triple $(\mathbf{c}, \hat{\tau}, \hat{\tau}^*)$ where $\hat{\tau}$ is a change in U.S. import tariffs on goods from a set of foreign countries $\mathbf{c} \subseteq F$, and $\hat{\tau}^*$ is the tariff change applied to U.S. goods in all foreign countries. The bilateral trade shock corresponds to $\mathbf{c} = F$ and $\hat{\tau}^* = \hat{\tau}$, whereas the China shock is parameterized by $\mathbf{c} = \text{China}$ and $\hat{\tau}^* = 0$. Negative values of $\hat{\tau}$ and $\hat{\tau}^*$ indicate liberalizations.

Defining Welfare. To evaluate welfare changes in a way that is comparable across agents, we follow the standard approach in the literature by using a money metric for utility: \hat{U}_i is defined as the equivalent variation EV_i divided by original expenditures X_i (Theil 1975; Deaton 1989; Fajgelbaum and Khandelwal 2016; Nigai 2016). For example, \hat{U}_i is equal to 0.01 if the trade liberalization is equivalent, in utility

¹¹In complementary analyses discussed in Section 7.3, we also run counterfactuals based on observed trade shocks, including the import tariffs introduced by the Trump administration in 2018.

¹²Following most of the trade literature, we ignore revenues generated by tariffs. For a recent treatment on the distinction between tariffs and generic iceberg trade costs, see Felbermayr et al. (2015).

terms, to increasing total spending by 1% at the original prices.

For small shocks, the envelope theorem (Roy’s identity) implies that price reductions benefit each type of consumer in proportion to their spending share for this industry, regardless of the demand system:

$$\hat{\mathcal{U}}_i \equiv \frac{EV_i}{X_i} = \hat{w}_i - \sum_j s_j^i \hat{p}_j \equiv \hat{w}_i - \hat{\pi}_i, \quad (2)$$

where $\hat{\pi}_i$ is the Laspeyres price index. Intuitively, because consumers are optimizing, re-optimization of expenditure shares in response to small changes in relative prices has only a second-order effect on welfare. The first-order effect comes from the expenses the agent saves by paying lower prices, holding spending shares constant.

From (2), differential gains between two skill groups can be decomposed into components related to changes in prices and wages, which we call the expenditure and earnings channels:

$$\hat{\mathcal{U}}_S - \hat{\mathcal{U}}_U = \underbrace{-(\hat{\pi}_S - \hat{\pi}_U)}_{\text{Expenditure channel}} + \underbrace{\hat{w}_S - \hat{w}_U}_{\text{Earnings channel}}. \quad (3)$$

Positive values indicate the effects that favor the skilled group (“pro-skilled”), and both channels are invariant to the choice of the numeraire. Average welfare gains admit a similar representation as the difference between average wage growth and inflation. Using bars for economy-wide averages,

$$\hat{\mathcal{U}} = \hat{w} - \hat{\pi} \equiv [\bar{v}\hat{w}_S + (1 - \bar{v})\hat{w}_U] - \sum_j s_j^{\text{Final}} \hat{p}_j, \quad (4)$$

where $\hat{\mathcal{U}}$ is the total equivalent variation relative to total expenditures, \bar{v} is the income share of the skilled group in the original equilibrium and $s_j^{\text{Final}} = \frac{X_j^S + X_j^U}{\sum_j (X_j^S + X_j^U)}$ is the share of j in total final spending.

2.2 Welfare Effects of Trade

We now characterize the average and differential welfare effects of counterfactual trade shocks in two steps. First, we treat wage changes as given and solve for the price changes induced by the shock. Second, we use the labor market clearing condition and demand structure to solve for wage changes.

Step 1: Price Changes Conditional on Wage Changes. Deriving price changes is easy in our model because of perfect competition. First, markups are constant (zero), so prices are determined by marginal costs with a complete pass-through rate. Second, supply is perfectly elastic, so marginal costs are determined by factor prices and not directly affected by demand conditions. Therefore import prices change one for one with the import tariffs, which are effectively a change in cost for foreign producers. Domestic prices are also shaped by costs, i.e. domestic wages. By the envelope theorem (Shephard’s

lemma):

$$\begin{aligned}\hat{p}_{jH} &= v_j \hat{w}_S + (1 - v_j) \hat{w}_U \\ &= \hat{w} + (v_j - \bar{v}) (\hat{w}_S - \hat{w}_U),\end{aligned}\tag{5}$$

where $v_j = w_S L_j^S / VA_j$ is the share of value added paid to skilled workers (a model-consistent measure of skill intensity) and value added is defined as $VA_j = w_S L_j^S + w_U L_j^U$ (which coincides with payroll in our model without capital).

To a first order, the change in the consumer price index in each industry combines import and domestic price changes, with weights governed by the import penetration rates:

$$\hat{p}_j = IP_{j\mathbf{c}} \hat{\tau} + (1 - IP_j) (\hat{w} + (v_j - \bar{v}) (\hat{w}_S - \hat{w}_U)),\tag{6}$$

where $IP_{jc} = X_{jc}/X_j$ is the market share of country c variety in industry j (“import penetration”), $IP_{j\mathbf{c}} = \sum_{c \in \mathbf{c}} IP_{jc}$ is total market share of varieties affected by the trade liberalization, and $1 - IP_j = 1 - \sum_{c \in F} IP_{jc}$ is the domestic share. Plugging the price formulas above into our expressions for the average gains from trade and the expenditure channel yields:

$$\hat{U} = \mathbb{E}_{\text{Final}} [IP_{j\mathbf{c}}] \cdot (-\hat{\tau}) + \mathbb{E}_{\text{Final}} [IP_j] \cdot \hat{w} - \mathbb{E}_{\text{Final}} [(1 - IP_j) (v_j - \bar{v})] \cdot (\hat{w}_S - \hat{w}_U),\tag{7}$$

$$-(\hat{\pi}_S - \hat{\pi}_U) = \Delta_{\text{Final}} [IP_{j\mathbf{c}}] \cdot (-\hat{\tau}) + \Delta_{\text{Final}} [IP_j] \cdot \hat{w} - \Delta_{\text{Final}} [(1 - IP_j) (v_j - \bar{v})] \cdot (\hat{w}_S - \hat{w}_U),\tag{8}$$

where $\mathbb{E}_{\text{Final}} [z_j] = \sum_j s_j^{\text{Final}} z_j$ is the cross-industry average of variable z_j with total final consumption weights and $\Delta_{\text{Final}} [z_j] = \sum_j s_j^S z_j - \sum_j s_j^U z_j$ denotes the difference between averages in the consumption baskets of the two groups.

Equations (7) and (8) show that the average welfare effect and the expenditure channel are governed by the same three forces. First, an import tariff reduction ($-\hat{\tau}$) directly makes the affected imported varieties cheaper, which benefits a consumer in proportion to her spending share on these imports. Second, an increase in domestic wages (\hat{w}) relative to foreign wages makes *all* imports more affordable; this channel benefits a consumer in proportion to her overall spending on imports. Finally, an increase in the skill premium ($\hat{w}_S - \hat{w}_U$) hurts consumers of skill-intensive domestic varieties, which we call the “segregation channel.”¹³

We note that if the segregation channel is negligible (as we will find in the data) and a trade liberalization affects all countries, then the strength of the expenditure channel, expressed as a fraction of the average welfare gains, is determined solely by the difference in spending shares on imports, again relative

¹³This force generates distributional effects if the economy is “segregated,” that is if each group of agents tends to consume from industries where they are predominantly employed. Specifically, a rise in the skill premium is partially dissipated through the expenditure channel in a segregated economy, as the goods consumed by skilled individuals become relatively more expensive. The same force generates aggregate gains or losses if total domestic demand is skewed towards high or low skill-intensive industries, compared with export demand.

to the average:

$$\frac{-(\hat{\pi}_S - \hat{\pi}_U)}{\hat{U}} = \frac{\Delta_{\text{Final}} [IP_j]}{\mathbb{E}_{\text{Final}} [IP_j]}.$$

Step 2: Solving for Wage Changes. To solve for wage changes, we proceed in three steps. We first use the labor market equilibrium to relate wage changes to growth in value added across industries. Then we use the demand system to characterize growth of each industry as a function of tariff and wage changes. These steps produce a system of equations for wage changes, which we solve in the final step.

Step 2a: Connecting Wages to Industry Sizes. We start with a simple observation: total value added in all industries is by definition equal to the average wage times the labor supply (total number of workers). Labor supply is fixed, so the change in the average wage equals the change in total value added, which is the weighted average of industry growth rates with (pre-shock) value added as weights:

$$\hat{w} = \frac{\sum_j VA_j \cdot \widehat{VA}_j}{\sum_j VA_j} \equiv \mathbb{E}_{VA} [\widehat{VA}_j]. \quad (9)$$

We obtain a similar representation for the change in the skill premium (proved in Theory Appendix A.1). Intuitively, if industries that are more skill-intensive expand faster, the relative demand for skilled labor grows. In equilibrium, labor supply is fixed, so this change in the relative demand has to be offset by a growing skill premium (which makes all industries switch from high-skilled to low-skilled workers). Formally,

$$\hat{w}_S - \hat{w}_U = \frac{\Delta_{VA} [\widehat{VA}_j]}{\sigma_{\text{within}}}, \quad (10)$$

where $\Delta_{VA} [\widehat{VA}_j] = \sum_j e_S^j \widehat{VA}_j - \sum_j e_U^j \widehat{VA}_j$ is the difference in the growth rates of industries where the skilled and unskilled work (using payroll weights) and σ_{within} is the elasticity that captures labor substitution within all industries given by $\sigma_{\text{within}} = 1 + \mathbb{E}_{VA} \left[\frac{v_j(1-v_j)}{\bar{v}(1-\bar{v})} \cdot (\sigma_j - 1) \right]$, where σ_j is the local elasticity of substitution between labor types in domestic industry j .

Step 2b: Solving for Changes in Industry Sizes Conditional on Wage Changes. In Step 1, we solved for the price changes induced by trade shocks, conditionally on wage changes. We now map these price changes into changes in industry output using the demand system (of each skill group as well as foreign buyers); without input-output linkages, output equals value added. We express industry growth as a sum of four terms:

$$\widehat{VA}_j = \eta_{jc}^{\text{import}} \cdot \hat{\tau} + \eta_j^{\text{export}} \cdot (-\hat{\tau}^*) + \eta_j^{\text{avg wage}} \hat{w} - \eta_j^{\text{skill prem}} (\hat{w}_S - \hat{w}_U). \quad (11)$$

The first two terms capture the expansion of domestic production as import tariffs grow and exporting barriers fall, holding wages fixed. The other two terms represent the response of demand to wage changes, which affect both purchasing power and domestic prices. Log-linearizing demand, Theory Appendix A.1

characterizes the corresponding elasticities:

$$\eta_{jc}^{\text{import}} = \text{Dom share}_j \cdot \left[(\xi_j - 1) \cdot IP_{jc} + (\varepsilon_r - 1) \cdot (\mathbb{E}_{\text{Final}} [IP_{jc} | r] - IP_{jc}) + (\rho - 1) \cdot (\mathbb{E}_{\text{Final}} [IP_{jc}] - \mathbb{E}_{\text{Final}} [IP_{jc} | r]) - (\psi_j - 1) \cdot \mathbb{E}_{\text{Final}} [IP_{jc}] \right], \quad (12a)$$

$$\eta_j^{\text{export}} = \text{Export share}_j \cdot (\xi_j - 1), \quad (12b)$$

$$\eta_j^{\text{avg wage}} = \text{Dom share}_j - \eta_{jF}^{\text{import}} - \eta_j^{\text{export}}, \quad (12c)$$

where $\text{Dom share}_j = 1 - \text{Export share}_j$ is the share of domestic consumers in the domestic industry output and $\mathbb{E}[\cdot | r]$ denotes a sectoral average.¹⁴ We now discuss these three expressions in turn.

Equation (12a) shows the different channels governing the response of industry value added to a change in domestic import tariffs. Falling domestic import tariffs ($\hat{\tau} < 0$) lower import prices, which drives the consumer price index down in proportion to import penetration. This leads to reallocation of spending between domestic and foreign varieties within each industry, captured by the first term in equation (12a), which we call the *import competition effect*. In our nested demand system, a change in consumer prices also affects demand at each tier of industries. Specifically, if $\varepsilon_r > 1$, spending is reallocated towards industries with more imports relative to their sectors, while complementarity between goods and services ($\rho < 1$) makes consumers spend more on services. These *substitution effects* are captured by the two middle terms. The last term in (12a) is the *income effect*: gains from trade, which depend on the average spending on imports $\mathbb{E}_{\text{Final}} [IP_{jc}]$, lead to higher spending on income-elastic industries. All of these effects only influence domestic consumption, so they are scaled by the domestic share of industry sales.

Equation (12b) depicts how industry value added responds to reductions in foreign import tariffs ($\hat{\tau}^*$). As foreign import tariffs fall, export demand grows according to the trade elasticity $\xi_j - 1$, contributing to industry output growth in proportion to the export share. The simplicity of this term relies on the fact that foreign prices and wages do not change.

Finally, industry size responds to changes in domestic wages according to equation (12c). Growing average wage raises purchasing power and thus demand, captured by the first term in (12c). However, growing wages also raise domestic prices, making domestic varieties less attractive both at home and abroad. This reduces the demand for domestic varieties in the same way as falling import tariffs and growing exporting barriers would, as shown by the last two terms in (12c).

Step 2c: Wage Changes in General Equilibrium. The last step of our analysis brings together the preceding formulas to account for feedback effects between price changes and wage changes in general

¹⁴To preserve space, the expression for $\eta_j^{\text{skill prem}}$ is given by (A15) in the online Appendix. To facilitate exposition, two quantitatively negligible adjustment terms are dropped from η_j^{import} , as described in Theory Appendix A.1 (see (A14)).

equilibrium. Formally, equations (9), (10), (11) form a linear system. Solving it, we obtain:¹⁵

$$\hat{w} = \left(\mathbb{E}_{VA} \left[\eta_j^{\text{import}} \right] \hat{\tau} + \mathbb{E}_{VA} \left[\eta_j^{\text{export}} \right] \cdot (-\hat{\tau}^*) \right) \cdot \text{Multiplier}, \quad (13a)$$

$$\hat{w}_S - \hat{w}_U = \left(\Delta_{VA} \left[\eta_j^{\text{import}} \right] \hat{\tau} + \Delta_{VA} \left[\eta_j^{\text{export}} \right] \cdot (-\hat{\tau}^*) + \Delta_{VA} \left[\eta_j^{\text{avg wage}} \right] \hat{w} \right) / \sigma_{\text{macro}}, \quad (13b)$$

where

$$\text{Multiplier} = 1 / \left(1 - \mathbb{E}_{VA} \left[\eta_j^{\text{avg wage}} \right] \right) \quad (14)$$

and $\sigma_{\text{macro}} = \sigma_{\text{within}} + \Delta_{VA} \left[\eta_j^{\text{skill prem}} \right]$.

Equation (13a) shows that a reduction of domestic (foreign) import tariffs decreases (increases) demand for domestic goods, which reduces (increases) domestic income. The direct effects of changes in domestic and foreign import tariffs on the average wage are magnified by a multiplier effect. This effect is conceptually similar to a local fiscal multiplier (e.g., Chodorow-Reich 2018): if domestic income goes up because of additional spending from foreign, domestic spending goes up and induces a feedback loop.¹⁶

Equation (13b) shows that three effects are at play in the earnings channel: the skill premium goes up if skilled workers tend to work in industries that shrink less after the fall in domestic import tariffs ($\Delta_A \left[\eta_j^{\text{import}} \right] < 0$), or that expand as a result of export opportunities ($\Delta_{VA} \left[\eta_j^{\text{export}} \right] > 0$), or that expand more as a result of a growing average wage ($\Delta_{VA} \left[\eta_j^{\text{avg wage}} \right] > 0$).

The effects entering the earnings channel are all scaled by the endogenous macro elasticity of labor substitution σ_{macro} . Intuitively, if skilled and unskilled workers are more substitutable, a smaller increase in the skill premium is sufficient to compensate the change in labor demand induced by trade and to restore the labor market equilibrium. σ_{macro} generalizes the macro elasticity of substitution between factors derived by Oberfield and Raval (2014) to the open economy and to a more flexible preference structure. Theory Appendix A.1 provides further discussion of σ_{macro} .

Our theoretical results on the earnings channel can be connected to the data as follows. Plugging (12a)–(12c) into (13b), one can see that differential exposure of the two skill groups to import competition ($\Delta_{VA} [IP_{jc}]$), exports ($\Delta_{VA} [\text{Export share}_j]$) and income-elastic industries ($\Delta_{VA} [\psi_j]$) plays a key role in how the skill premium responds to trade shocks. Our reduced-form analysis of the earnings channel thus focuses on measuring these statistics, while for the calibration we supplement them with structural elasticities (e.g., trade elasticities) as prescribed by the model.¹⁷

¹⁵To derive these expressions, we make the approximation $\mathbb{E}_{VA} \left[\eta_j^{\text{skill prem}} \right] \cdot (\hat{w}_S - \hat{w}_U) \approx 0$, ignoring the impact of the skill premium change on the average wage. We have verified in the calibration that this impact is quantitatively negligible. Without this approximation, the solution to the system, presented in the Theory Appendix A.1, becomes less transparent.

¹⁶This feedback loop is a result of three mechanisms, corresponding to the terms in (12c). When nominal income grows, spending by domestic consumers raises output according to its domestic share. However, wage growth also raises the prices of domestic goods, which makes them less attractive relative to imports and also in export markets. In our calibration, we find that these price effects (labeled “expenditure switching effects” in Chodorow-Reich 2018) substantially weaken the feedback loop.

¹⁷In calibrations we will follow the model exactly, for instance measuring $\Delta_{VA} [\text{Dom share}_j \cdot (\xi_j - 1) IP_{jc}]$ instead of $\Delta_{VA} [IP_{jc}]$ as the effect of import competition. However, $\Delta_{VA} [IP_{jc}]$ is more useful to build intuition, which is our goal in the reduced-form analysis.

2.3 Model with Input-Output Linkages

We now turn to the role of input-output linkages. When measuring differences in import spending and exposure to the labor market effects of trade, it is important to account for intermediate inputs, both because trade in intermediates is increasingly important (Feenstra and Hanson 1996) and because value added, final consumption, and gross output are substantially different from each other in the data. We follow the literature by assuming that production combines value added with intermediate inputs, which are composite goods from various industries, using a Cobb-Douglas aggregator (e.g., Caliendo and Parro 2015).

Theory Appendix A.2 provides the formal exposition of our full model, which differs from the model without input-output linkages in several ways. In the full model, the expenditure channel is governed by spending patterns on imported products (“direct imports”) but also on imported inputs embedded in domestic products (“indirect imports”). For the earnings channel, input-output linkages enrich the result in three ways. First, a fall in domestic import tariffs has a new effect: the prices of domestic products produced with imported inputs fall, which raises demand for these products. Consequently, the skill premium falls if college graduates work in industries that use fewer imported inputs. Second, the strength of the substitution and income effects is determined by both direct and indirect imports. Finally, all shocks propagate upstream. For example, increased export demand for a final good raises demand for its inputs, whose production grows accordingly, which causes further expansions upstream. As a result, the export share driving the industry expansion includes exports of the industry itself but also of its downstream buyers (we refer to it as “input-output adjusted”). The same logic applies to import penetration. Similarly, income effects increase industry size according to the weighted average of income elasticities of the industry itself as well as the domestic final industries which buy its output.

2.4 Discussion

At this stage, it is instructive to discuss what we view as the main limitations of our theoretical framework.

For the expenditure channel, our demand system is homothetic across varieties within each industry, precluding within-industry differences in consumption across groups. We view this as an aggregation issue that would not arise if the product space was sufficiently refined in the data. We will therefore measure the model-relevant statistics, such as the difference in import spending across groups, combining *all* available data, both across and within industries. Second, we made the key assumption that the pass-through of trade costs into prices is complete. Empirical evidence suggests this assumption may be violated in practice (e.g., De Loecker and Warzynski 2012; De Loecker et al. 2016), but this violation would introduce a bias only if pass-through was systematically different across industries selling to different groups of consumers. The estimates of Bai and Stumpner (2018) suggest this is not the case empirically. Moreover, recent work suggests that endogenous markups may not have large effects on the total pass-through of shocks into consumer prices because of offsetting effects on domestic and import prices (Arkolakis et al. (2017) and Amiti et al. (2018b)). Third, it may appear that we need to track global value chains and remove

U.S. value added from U.S. imports. In fact, this is not necessary: when import tariffs or transportation costs increase in our counterfactuals of interest, they apply to the full value of imports, including the components originally produced at home (unless special provisions of the tariff schedule, such as the Offshore Assembly Provision, apply; cf. [Finger 1976](#)).

For the earnings channel, we have made four substantive assumptions that are potentially restrictive in light of the literature. First, we have assumed away that import competition may be “skill-biased” *within* an industry; in fact, firms that have lower skill intensity may be more affected by import competition (e.g., [Bernard et al. \(2006\)](#), [Krugman \(2008\)](#)). Second, our treatment of intermediate inputs does not take into account the potential role of offshoring (e.g., [Grossman and Rossi-Hansberg \(2008\)](#)), which could predominantly affect low-skill workers. Third, our assumptions on the production function imply that a fall in the cost of imported intermediate inputs for an industry benefits workers in that industry through increased output, precluding the possibility that workers are substituted for intermediate inputs and labor demand falls. Although empirical evidence is mixed (e.g., [Acemoglu et al. \(2016b\)](#)), such substitution may be more relevant for low-skill workers. Fourth, we have assumed perfect mobility of workers across industries, while empirical evidence indicates that mobility is limited in particular for low-skill workers, at least in the short to medium run (e.g., [Autor et al. \(2014\)](#)).

In the Theory Appendix, we show how to extend our framework to account for skill-biased import competition by building on [Borjas et al. \(1997\)](#) (Section [A.3](#)) and how to accommodate imperfect mobility using a Roy model (Section [A.4](#)).¹⁸ In the baseline analysis, we abstract from these issues to keep the model parsimonious and disciplined by the available data. Since the four channels described above are likely to hurt unskilled workers relatively more, our baseline estimates can be interpreted as a lower bound for the effect of trade on inequality.¹⁹

3 Industry-Level Differences in Spending on Imports Across Consumer Groups

To estimate differences in import spending across consumer groups, one would ideally collect data on expenditure shares and import content by individual product. But constructing such a dataset is infeasible; instead, in this section we use data on 372 detailed industries covering all goods and services to capture the *across-industry* component of the difference in import spending. We leave the investigation of within-

¹⁸The Roy extension shows that even with imperfect labor reallocation and within-group income differences, (i) trade only impacts nominal income inequality through changing the average skill-premium and (ii) the average skill premium is still determined by $\Delta_{\text{Final}} \left[\widehat{VA}_j \right]$, as in equation (10).

¹⁹Our theoretical framework can accommodate other potential limitations. First, we do not take explicitly into account the role of expanding product variety for the expenditure channel, while empirically the extensive margin appears to matter substantially for price effects (e.g., [Amiti et al. \(2018a\)](#)). As previously mentioned, our formulas still apply for a class of trade models with extensive margin effects as in [Eaton and Kortum \(2002\)](#). Other standard settings with extensive margin effects such as [Krugman \(1980\)](#) and [Chaney \(2008\)](#) can be nested in our framework by adding economies of scale ([Kucheryavyy et al. 2018](#)). Second, although we focus on a first-order log-linear approximation, the model structure can be used to study large trade shocks. Finally, offshoring and skill-biased effects of intermediate inputs could also be potentially accommodated by building on [Goos et al. \(2014\)](#).

industry differences to Sections 4 and 5. We find that spending on imports (both direct and indirect) is similar between education groups, close to the national average of 12.6%, which implies that the expenditure channel is distributionally neutral at the level of industries.

3.1 Data

We conduct the analysis based on a detailed merge of the Consumer Expenditure Survey (CEX) to the Input-Output (I-O) table from the Bureau of Economic Analysis (BEA). Column (1) of Table 1 presents summary statistics on the linked dataset, which we build in a series of steps, described in the remainder of this section. The CEX measures personal spending for over six hundred detailed categories, covering all categories of goods and services, and records consumers’ characteristics such as education and income. We merge the CEX to the BEA I-O table to obtain information on domestic production and trade. Specifically, we build a manual concordance from 660 CEX consumption categories into 170 final industries in I-O. Data Appendix B.1 provides more details on the CEX sample and crosswalk.

BEA data are the most detailed available accounts of the entire U.S. economy, including non-manufacturing industries; the most recent detailed I-O table, which includes 389 industries, dates from 2007, so we center the analysis around that year (combining CEX data for 2006–08 to increase sample size). We use the I-O table in three ways: as a source of import shares, input-output linkages, and consumption structure. First, for each industry we compute the import penetration as a percentage of absorption (defined as output plus imports minus exports). There are two advantages of using the BEA data to measure import penetration: trade in services is accounted for and trade flows are measured from the same data as domestic output, which improves consistency. Second, we build the input requirement matrix, which measures the composition of suppliers for each buying industry. We use it to construct the share of indirect imports (imports of intermediate inputs) used in domestic production. Combining direct and indirect imports, we obtain the total import content of absorption. Finally, we use personal final consumption from the I-O table as a measure of total spending in the industry, which we then decompose into consumption by education group using the CEX. This approach parallels [Lebow and Rudd \(2003\)](#) who show that reweighting the CEX using BEA spending shares yields more accurate inflation estimates, correcting non-classical measurement error in the CEX (e.g., [Garner et al. 2009](#)).²⁰

It is important to account for “distribution margins” to accurately compute the share of imports in total absorption. The distribution margin refers to the cost of retailing, wholesaling, and transportation, which by definition have a low import content. For example, when consumers buy apparel, much of their spending is effectively devoted to distribution margins. The I-O table reports that imported final products constitute 84% of total absorption in the apparel industry; when accounting for domestic distribution costs, the total import content shrinks to only 38%. We implement this adjustment for all industries

²⁰Measurement error in the CEX does not create biases for our results as long as it has the multiplicative structure proposed and justified by [Aguiar and Bils \(2015\)](#): there may be industry- and consumer group-specific biases but no interactions between them. Industry-specific biases are corrected by the BEA weights, while consumer-group-specific biases only result in a re-scaling of consumption across groups without systematic effects on the expenditure composition of each group.

using the information available from the I-O table. We aggregate several retailing and transportation industries due to data availability, compute all I-O-related objects for the resulting 381 industries, and drop 9 special industries (five government industries, Scrap, Used and secondhand goods, Noncomparable imports, and Rest of the world adjustment). Our final sample thus consists of 372 industries, including 170 merged to the CEX. Data Appendix B.2 provides additional details on input-output tables and on the data construction, including the treatment of distribution margins.

To characterize which groups of industries drive the effects we will document, we classify industries into sectors and sub-sectors. Manufacturing, agriculture, and mining are classified into goods and all other industries into services. Goods and services are further classified into 24 and 15 subsectors, respectively, which are listed in online Appendix Table A2.

To conduct the analysis for specific trading partners, we need to merge additional trade data. The I-O table provides total imports for each industry but does not decompose them into countries of origin. We measure import penetration from China, NAFTA countries (Mexico and Canada), and 34 developed economies (OECD members, excluding NAFTA, plus Taiwan and Singapore) using the 2007 U.S. international trade flows statistics from the Census Bureau by product and source country, which were made available by Schott (2008) and converted into NAICS industry codes by Pierce and Schott (2012). We follow the same strategy as with the consumption data: we keep total imports from the I-O table, which are consistent with the rest of the I-O table, but distribute them across countries of origin using the trade statistics. For each I-O industry, the import penetration from a specific trading partner is computed as the product of total I-O-based import penetration and the fraction of this trading partner in total imports in the NAICS codes that belong to this I-O code.²¹ Armed with this merged dataset, we turn to the computation of import spending shares by education group.

3.2 Baseline Results and Mechanisms

We find that spending shares on imports are very similar for consumers with and without a college degree. Table 2 provides the main estimates on the average and differential spending on imports, decomposing the latter into within- and between-components. The first row shows that the total expenditures of U.S. consumers in 2007 includes 12.6% of imports (column (1)), of which 6.9 p.p. are direct imports (column (2)) and 5.7 p.p. are indirect imports via imported intermediate inputs. The overall spending share on imports is slightly lower than the imports-to-expenditures ratio, which is 14.7%, because some imports are used in the production of exports (and because non-comparable imports have been excluded). The following rows compute average spending on imports for consumers with and without a college degree. College graduates devote 12.2% of their spending to imports, as opposed to 12.8% for consumers without a college degree. College graduates therefore benefit less when imports become cheaper, but the difference

²¹Trade flow statistics are available only for trade in goods. We therefore assign zero imports from the specific trading partners of interest in all service industries. This does not constitute an important limitation for China and Mexico. For instance, China constitutes less than 3% of total U.S. imports of services according to the BEA International Services tables for 2007. This limitation is likely to be more important when considering trade with developed economies.

is small, only 0.60 p.p., or 4.8% of the average.²² This difference comes from both direct imports (0.20 p.p.) and indirect import spending (the remaining 0.40 p.p.).

The small observed difference in spending shares on imports across education groups is partly a consequence of two offsetting patterns. On the one hand, college graduates consume more services as a fraction of total expenditure than consumers without a college degree, and services are much less imported than goods. If the consumption baskets of the two groups were identical within goods and within services, the import spending share for college graduates would have been 1.02 p.p. lower than for individuals without a college degree.²³ On the other hand, within goods and services college graduates spend relatively more on industries with a higher import share, which reduces the difference substantially (by 0.42 p.p.). Table 2 also shows that most of the differences within goods and within services (0.31 out of 0.42 p.p.) result from differences in spending patterns across 29 subsectors, while within-subsector heterogeneity is relatively unimportant.

The difference in spending on imports across education groups within goods is a robust pattern, which can be assessed graphically. Panel (a) of Figure 1 shows the relationship between the industry share of sales to college graduates and its import content. Each dot represents 5% of detailed industries within goods or services (with final consumption weights) and the figure shows that the patterns are not driven by a small number of industries: there is a strong positive slope for goods and none for services. The interpretation of this graph relies on the fact that the share of spending on imports is higher for college-educated *consumers* if and only if *industries* that sell relatively more to college graduates have higher import content (see Theory Appendix A.5 for a formalization of this equivalence).

We characterize graphically the parts of the product space contributing to the within-sectoral differences in spending on imports in favor of college graduates. Panel (b) of Figure 1 groups industries by subsectors, where the size of each circle indicates their importance in final expenditures. “Food” and “Computers and electronics” are characteristic subsectors within the goods sector: while food is purchased relatively more by non-college consumers and does not have much imports, electronics are represented disproportionately in the consumption basket of college graduates and have a very high share of imports.

We obtain qualitatively similar patterns, with small differences in spending on imports across education groups, when considering trade with specific partners. Columns (3)–(8) of Table 2 show statistics for spending on imports from three sets of countries: China, NAFTA, and developed economies. College graduates spend 0.13 p.p. *more* on imports from China: this finding is explained, in part, by imports of electronics, for which China is a key trading partner (see online Appendix Figure A2). Consumers without a college degree spend more on imports from NAFTA and developed economies (0.24 p.p. and

²²This difference is statistically significant. Inference here is based on the randomness of the CEX sample. Error in the industry import penetration is non-statistical (e.g. due to imputations required to prepare input-output tables) and is not taken into account. When we use total spending from the CEX as a measure of total spending in the industry (instead of I-O personal consumption weights), we similarly find that college graduates spend 14.5% on imports, versus 15.8% for consumers without a college degree, with a difference of 8.1% of the average.

²³Services constitute 70.3% (66.0%) in consumption baskets of individuals with (without) a college degree. A similar pattern across income groups was established by Boppart (2014). The average share of imports is 28.8% for goods and 4.9% for services. See online Appendix Table A3 for the estimates and Theory Appendix A.5 for the within-between decomposition formula.

0.25 p.p., respectively), which is almost entirely due to their higher spending on goods, rather than to differences within goods.

3.3 Robustness and Extensions

We conclude this section by reporting additional results that document the expenditure channel for various socio-demographic groups and over time, and investigate the segregation channel as well as the role of exports.

First, we find that spending shares on imports are also very similar across income groups. In Figure 2, we compare spending shares on imports across bins of household income, overall and from China, NAFTA, and developed countries specifically. In all cases, we find relatively flat patterns, although the relationship between income and spending share on imports is slightly increasing for imports from China and slightly decreasing for imports from developed economies.²⁴ Online Appendix Figure A4 shows the stability of the patterns across education and income groups over time using data on 71 more aggregated industries. In each year between 2002 and 2015, the spending shares on imports were very similar for these groups.

Second, Figure A5 shows that the fraction of spending on imports is also similar across other socio-demographic groups: more detailed education groups, age groups, households who live in different regions, in the states that voted for Hillary Clinton vs. Donald Trump in 2016, households who are homeowners or not, or who differ by household size.

Third, besides differences in import spending across consumer groups, the expenditure channel can be generated in our model by differences in the skill intensity of consumption baskets, through the segregation channel. Robustness Appendix D.1 and Figure A6 investigate the empirical relevance of this channel. We find that differences in skill intensity between college and non-college consumption baskets are small, implying that the distributional effects from trade through the segregation channel are negligible.

Finally, we have considered the role of exports. In our model, differences in export intensity between consumption baskets do not play a role because, in the absence of scale effects, exporting shocks do not affect goods prices conditional on wages. Empirically, we have verified that differences in export intensity between the college and non-college consumption baskets are also very small (within 3% of the average, with or without I-O adjustments).

In sum, considering spending patterns across 170 categories of final consumption, we have shown that consumers of different education or income levels have similar spending shares on imports, whether overall or from specific trading partners. Our analysis so far suffers from a potential aggregation bias: for instance, it could be the case that the low-skill group consumes a larger fraction of imported varieties *within* categories. We now turn to this question and provide evidence that there is no such pattern for consumer packaged goods (Section 4) and automobiles (Section 5).

²⁴Since spending shares are flat but richer households have higher expenditures, the dollar amount spent on imports is increasing in income, as reported in online Appendix Figure A3. Therefore, in absolute dollar value, the expenditure channel favors richer households.

4 Differences in Spending on Imports within Consumer Packaged Goods

In this section, we examine within-industry spending on imports for consumer packaged goods (goods typically purchased in supermarkets); we do so by creating a firm-level dataset in which we observe both consumer characteristics and import content. Column (2) of Table 1 presents summary statistics on this linked dataset, whose construction is described in detail below. We find that college graduates buy relatively more imports, except from China; but the differences are small. Expressed as a percentage of average spending on imports, the difference between consumers with and without a college degree is less than 5%.

4.1 Data

We start from the Nielsen Homescan Consumer Panel (henceforth Nielsen), which measures spending at the level of barcode and provides consumer characteristics such as education and income. This dataset does not provide information about whether a product was produced domestically or imported; it is also uninformative about the share of imported inputs embedded in domestic products. We address both problems at once by linking products (barcodes) to their producers or distributors in the U.S. Economic Census and Customs microdata. We proxy for a product’s import content by the share of imports in total sales for the linked firm thus capturing imports of both final products and intermediate inputs (except those imported through a domestic intermediary). We find Census matches for the majority of Nielsen firms, excluding small firms, and cover over 80% of total Nielsen sales.²⁵

The Nielsen data cover three classes of products: (i) food, alcohol, and tobacco (henceforth “food”), (ii) health, beauty, and household products (henceforth “health and household”), and (iii) general merchandise, namely other products found in supermarkets such as tableware, stationery, or electronics. These products are classified into 10 departments (e.g. Frozen Foods), 117 product groups (e.g. Frozen Prepared Foods), and 1,165 product modules (e.g. Frozen Soup). To study within-industry differences in import spending in a way consistent with the industry-level analysis of Section 3, we manually convert modules into 71 detailed I-O industry codes.²⁶

We attribute barcodes to firms using information from GS1 US, a non-profit organization that maintains the barcode system. To sell products in supermarkets, a manufacturer or a distributor has to purchase a block of barcodes from GS1; each barcode can only be registered by one firm. With a small fraction of exceptions, these firms have U.S. addresses—i.e., foreign firms do not tend to register barcodes without an affiliate or an intermediary in the U.S. In Data Appendix B.3, we track several products

²⁵We are aware of two alternative approaches to identify imported products in barcode-level data. First, the three leading digits of the barcode correspond to the country of its registration (Bems and Giovanni 2016). However, foreign firms often relabel their products locally for the U.S. market. Second, the country of origin can be manually inferred from some product labels (Antoniades and Zaniboni 2016) but the massive number of products sold in the U.S. makes this strategy infeasible for us.

²⁶Based on our crosswalk, Nielsen covers around 30% of expenditures on goods: it offers comprehensive coverage of at least food and beverages at home (25% of expenditures on goods in the I-O table), and those categories are around 72% of expenditures in Nielsen. For discussions of the share of overall consumption covered in Nielsen, see Broda and Weinstein (2010), Kaplan and Schulhofer-Wohl (2017), and Jaravel (2018).

photographed in a Walmart store to verify that domestically produced goods are normally registered by the manufacturer, while imported products are registered by the distributor, often a wholesaler.

We then link Nielsen data to three confidential datasets on American businesses collected by the U.S. Census Bureau. First, Business Register, or SSEL, provides a comprehensive list of firms and establishments; we use it as a source of names and addresses to merge firms in the Census with Nielsen. Second, our source of production data is the quinquennial Economic Census from 2007 and 2012, which includes Censuses of Manufactures, Wholesale, Retail, and other sectors. Because we are interested in imports of final products, which are often carried out by dedicated wholesalers or retailers, it is useful for us to observe establishments in the entire economy rather than only in the more commonly used Census of Manufactures. To reduce noise, we merge three years of the Nielsen data to each Economic Census: 2006–2008 for the 2007 Census and 2011–2013 for 2012. Finally, LFTTD is the transaction-level dataset on imports and exports of goods from the U.S. Customs, linked to the other databases by firm identifiers.

Merging firms between Nielsen and the Economic Census is a complex, multi-stage procedure. We use both exact and fuzzy matching rules on firm names and different components of the address: state, city, street, street number, and zipcode. We develop a set of consecutive merging rules and verify their quality by manual inspection of a sample of merged firms. Out of the total number of 23,300 Nielsen firm-years in 2007 and 2012, we successfully match 12,700, covering 83% of sales. Data Appendix B.3 provides details on the data sources, describes the matching process, and presents the match statistics.

Key Variables and Summary Statistics. We use Nielsen to measure total sales for barcodes and firms overall and by consumer education and income. To compute firm-level import content, we divide the value of imports from LFTTD by total sales of the firm in the Economic Census. The numerator includes imports of both final products (e.g., by wholesalers and firms with multinational production) and intermediate inputs, except those acquired through domestic intermediaries. As in Section 3, we also measure three components of the total import share, based on the imports from China, NAFTA, and 34 developed economies.

We adopt a square-root weighting scheme to reduce measurement error. As we cannot attribute a firm’s imports to a particular class of products it sells or even to Nielsen products overall, our proxy for the import content is likely to be noisier for large firms, which typically operate in multiple industries. Those same firms play a large role when measuring the average share of import spending for each consumer group, a consequence of the “granularity” featured in firm-level datasets (Gabaix 2011). Rescaling each firm’s Nielsen sales to its square root reduces the influence of poorly measured large firms.²⁷

Online Appendix Table A4 shows detailed summary statistics for the main variables used in the analysis at the level of firms by product modules, for all products together and split by the product class.

²⁷Granularity is a substantial challenge: in the full Nielsen sample, top 50 (200) firms capture 46% (70%) of sales in an average year; with square-root weights, they take up only 9% (21%). When decomposing firm sales, we allocate the total firm weight (square-root of sales) to different products and consumers proportionally to their fraction in the total sales, which ensures consistency of results across levels of disaggregation. In Robustness Appendix D.2, we verify the robustness of our results to other weighting schemes: unadjusted sales and sales raised to the powers 1/4 and 3/4.

The average spending on imports is 11.1%, with large differences across product classes, ranging from 6.9% for food to 14.6% for health and household and to 28.0% for general merchandize (with substantial variation across product modules within each class).

4.2 Results and Mechanisms

Table 3 measures the average share of spending on imports and the difference between Nielsen panelists with and without a college degree. Column (1) reports that imports constitute 11.1% of total expenditures, but this number is higher for college graduates than for consumers without a college degree: 11.5% and 10.9%, respectively. The pro-skilled difference of 0.59 p.p. is statistically significant and equals 5.4% of the average.²⁸

To make our Nielsen results complementary to the industry-level analysis, we need to avoid double-counting. Since the Nielsen sample covers multiple I-O industries, some of the 0.59 p.p. difference may stem from the composition of consumption across I-O industries, which has already been accounted for in Section 3. The “within industries” row of column (1) shows that double-counting is not a big issue: most of the difference (0.48 p.p.) is a consequence of differential spending on imports within the same industries. Moreover, around half of the total difference (0.28 p.p.) is within product modules, the most detailed classification available in Nielsen.

Panel (a) of Figure 3 graphically illustrates differences in import spending. This binned scatterplot groups firm-module cells by their consumer base—the share of college graduates in sales—and plots it against the average (firm-level) import share on the vertical axis. As shown in Theory Appendix A.5, the difference in the spending share on imports between the two groups can be expressed as the slope of this relationship multiplied by the consumption segmentation index—a measure of dissimilarity between the two consumption baskets. In this graph, we residualize the relationship on the I-O industry dummies to capture only the within-industry component of differential spending.

The figure shows that firms selling more to the college graduates import more. The slope is statistically and also economically significant: while firm-modules with less than 20% sales to college graduates have an average import share under 9%, the corresponding import share is around 12% for firm-modules with more than 40% of college-graduate sales. However, the slope of this relationship is not sufficient to generate big differences in import spending between groups, given the consumption segmentation index of 6.5%.²⁹

The remaining columns of Table 3 report average and differential spending on imports from China, NAFTA, and developed economies separately. The results are intuitive: almost all of the difference from column (1) is explained by imports from developed countries, with the difference reaching 17.6%

²⁸Unlike Section 3, the sample of households in Nielsen is much larger than the set of firms. Therefore, we develop and implement a different approach to inference that is based on the randomness in the sample of firms; see Econometric Appendix C.1.

²⁹This value of the segmentation index means that college graduates buy from firms which, on average, sell 6.5 p.p. more to them than the firms which non-college consumers buys from. Panel (a) of Figure 3 can be compared with Figure 2 from Jaravel (2018). Using similar Nielsen data, he finds that the relationship between product module-level inflation and the average consumer income is sufficiently strong to generate large differences in average inflation across groups.

of the average. College graduates also spend slightly more on imports from Canada and Mexico. At the same time, they spend around 4.4% less on Chinese products. Panels (b)–(d) of Figure 3 show the corresponding graphs. Online Appendix Table A5 verifies that the findings hold qualitatively in each of the three product classes: college graduates spend less on Chinese products (in particular for health and household products) and more on other imports (most strongly for food).

Thus, the within-industry patterns differ from those across industries (Table 2). College-educated consumers spend relatively more on industries where China is strong, in particular computers and electronics; cross-industry patterns are weaker for developed economies. In contrast, *within* consumer packaged goods college graduates buy slightly fewer varieties from China and more from developed countries.

A natural mechanism for the within-industry patterns we observe is related to product quality, which richer college graduates may value more (e.g., Fajgelbaum et al. (2011)). Although we do not model or measure quality explicitly, we can investigate this question empirically by proxying for quality with detailed barcode-level prices. 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.

Panel (a) of Figure 4 confirms that college graduates buy higher-priced products: moving from the lowest to the highest decile shifts the share of college consumers from 25% to almost 40%. The following panels of this figure locate imports in the distribution of prices. Products in the top deciles in their modules tend to have more imports from countries other than China, with most of the effect coming from developed countries (Panels (b) and (c), respectively). Conversely, imports from China in the Health and Household product class are substantially more prevalent at the bottom of the price distribution (Panel (d)). That pattern is not present for imports from China within General Merchandize (Panel (e)), which is consistent with weaker differences in spending between college and non-college consumers in that class (Online Appendix Table A5).

We find similar patterns across income groups. Figure 5 splits consumers into 15 household income bins (which is how income is reported in Nielsen) and measures the average spending on imports for them. The patterns are monotonic, with the fraction of non-China imports varying between 6.3% for the very poor to 7.6% for the very rich in all products covered by Nielsen (Panel (a)). Similarly, for China the fraction of imports falls monotonically with income from 6.8% to 6.4% for health and household products (Panel (b)) and from around 19% to 17.5% for general merchandize (Panel (c)). Because of the compositional differences across product classes (rich people buy relatively more general merchandize than food), the fraction of spending on Chinese products in the full sample is not decreasing in income (Panel (d)). This does not affect our results since we are interested in within-industry patterns.

Robustness Appendix D.2 presents additional findings and robustness checks. It shows that the differences we observe are driven by imports of final products (rather than intermediate inputs), and that the results are similar with other weighting schemes. Moreover, we develop a methodology to bound the attenuation bias that may arise because we only observe imports at the firm level, not for individual barcodes. Applying this methodology, we find that attenuation should not reduce the difference by more than 1.5 times, thus the difference in import spending would remain very small absent attenuation. The

key insight in this analysis is that the consumer base varies more across firms than across products within the firm. Finally, in Robustness Appendix D.1, we document that the segregation channel operating within the Nielsen sample does not generate substantial distributional effects.

Overall, we find that college graduates buy more imports, in particular from developed countries, but less of Chinese imports, consistent with differences in product quality. These differences are relatively small.

5 Differences in Spending on Imported Vehicles

This section shows that college graduates devote a larger fraction of their spending on motor vehicles (cars and light trucks, i.e. SUVs) to imported models. The difference is very large when considering direct imports of vehicles assembled outside of the U.S., Canada and Mexico. When imports of assembled cars from Canada and Mexico are included, the difference in import spending shares between education groups is reduced substantially, although it remains significant. In a robustness check using firm-level data from the Census, we show that college graduates spend less on indirect imports of automobiles (via car parts), but this difference is small and does not offset the direct imports patterns.

5.1 Data

To document spending on imported models of vehicles, we combine data from the CEX and Ward’s Automotive Yearbooks (averaging over years 2009–2015 to reduce noise in both datasets). Column (3) of Table 1 presents summary statistics on the linked dataset. The CEX data provide information at the level of brands: the CEX interview survey asks households to report the brands of the vehicles they own. Chevrolet and Buick are examples of such brands, which are more detailed than firms (Chevrolet and Buick are both produced by GM) but not as detailed as models (e.g. Chevrolet Camaro). We match each brand available in CEX to Ward’s Automotive Yearbooks, a leading publication for statistics on the automotive industry. The Ward’s data allow us to estimate the fraction of imported models within each brand (before investigating the role of imports of car parts in Subsection 5.3).

We define a model as imported if it was assembled outside of the U.S. Ward’s Automotive Yearbooks provide information on country of assembly for each model. More specifically, they report the fraction of cars assembled outside NAFTA in U.S. purchases; for vehicles assembled within NAFTA, the breakdown between those assembled in the U.S., Canada and Mexico is available. Most models are either only imported or only assembled domestically, but in a few cases assembly occurs both in the U.S. and abroad. In such cases, we treat the model as being “partly imported”: our proxy for its direct import share is simply the fraction of cars of this model that were assembled in Canada or Mexico (relative to NAFTA as a whole).

Our final sample includes 45 brands and 99,278 vehicles, 38.7% of which were purchased new.³⁰

³⁰Motor vehicles account for approximately 8% of personal expenditures according to the I-O table.

Online Appendix Table A6 lists the brands, and Data Appendix B.4 provides more detail on the data construction.

5.2 Results

We find that college graduates are more likely to purchase imported vehicles. Table 4 measures the average fraction of imported vehicles and the difference across education groups. Column (1) shows that on average 44.4% of purchased vehicles are assembled abroad, with a share of 47.7% for college graduates relative to 42.7% for those without a college degree. The spending share of college graduates on imported vehicles is thus 5.1 p.p. higher, or 11.4% of the average.

The differences in spending on imported vehicles between education groups vary substantially across trading partners. Columns (2) and (3) of Table 4 decompose imports into those from NAFTA and from other countries. Spending shares on imports from outside NAFTA are much higher for college graduates (24.7%) than for those who did not attend college (15.3%). Imports from Canada and Mexico offset about half of this effect: the spending share from college graduates is 4.3 p.p. lower in this sample.

The patterns are similar for new and used vehicles, as shown in columns (4) and (5). The last two columns of the table split the sample by the type of vehicle (cars vs. SUVs). We find that the difference in import spending is especially strong for cars, but it goes in the same direction for SUVs.

The robustness of these findings can be assessed graphically. Figure 6 plots import share against the fraction of sales to college graduates across brands, reporting the results separately for imports excluding NAFTA and total imports. Panel (a) shows a very strong positive relationship between imports excluding NAFTA countries and consumer education. Two clusters of brands become apparent: brands selling to college graduates are mostly high-end foreign brands (e.g. BMW, Lexus, and Mercedes-Benz), whereas brands selling to consumers without a college degree are almost all domestic (e.g. Chevrolet, Buick, and Dodge). Panel (b) shows that the total difference in import spending shares across education groups is weaker because of NAFTA: many domestic brands have 20 to 50% of their cars assembled in Mexico and Canada, creating a partially offsetting effect. Consistent with Table 4, the slope for total imports remains positive and significant in Panel (b).

Figure 7 shows that similar patterns hold across income groups, with a particularly strong pro-rich bias for non-NAFTA brands above the 80th percentile the income distribution. The figure reports spending shares on imports by bins of household income. As in Table 4, rich consumers buy more imported cars overall, which is driven by their spending on imports from outside NAFTA. The bias towards non-NAFTA imports is particularly strong at the higher end of the income distribution. The fraction of spending on these imports grows with income gradually from around 15% in the lower tercile to around 20% at the 80th percentile; then an inflection point is reached and the import share exceeds 30% at the very top of the income distribution.

5.3 Imports of Car Parts

Domestically assembled cars may use a substantial amount of imported parts, which the data we have used so far cannot capture: Ward’s reports only give information on the country of assembly. To address this potential issue, we use the confidential Census of Manufactures and the Customs import transactions data (LFTTD), where the fraction of both imported cars and car parts in the value of sales can be measured. For each auto manufacturer, we compute the “direct” import content as the ratio of imports of assembled cars measured in the Customs data to the value of car shipments from the Census. The “total” import content additionally includes imports of car parts in the numerator. Data Appendix B.4 describes the data construction in more detail. A downside of this approach is that we have to aggregate the sample from the level of brands to firms, overlooking the patterns of consumption and imports across brands of the same firm. For this reason, our main analysis is based on the CEX and Ward’s Automotive Yearbooks. Note that we do not need to eliminate the domestic value added of car imports, as discussed in Section 2.4.

Using the linked CEX-Census sample, we find that college graduates spend less on indirect imports of automobiles; but the difference is very small and does not outweigh the fact that they spend more on direct imports. Table 5 reports the results via regressions (data confidentiality does not allow us to show individual observations, like Figure 6 did). In columns (1) and (2), the dependent variables are direct and total imports (as a percentage of total new auto sales) and the regressor is the share of new cars sold to college graduates in the CEX. Columns (3) and (4) repeat the same exercise for used car sales. In both cases, the regression coefficient is reduced when indirect imports are taken into account, but by around 10% only. While these regressions may suffer from aggregation bias, because we are considering firms instead of brands, the comparison between the various columns strongly suggests that indirect imports do not have a substantial offsetting effect on differences in imports spending between education groups, thereby validating our baseline estimates.

Taking stock, the results from Sections 4–5 consistently find that more educated and richer individuals have a slightly higher share on imports *within* industries, which offsets the small reverse pattern *across* industries documented in Section 3. Data Appendix B.5 shows how to combine these results to produce a single estimate for the difference in import spending across groups, assuming that consumer packaged goods and vehicles are representative of other imported goods. The results, reported in Table A7, imply that college and non-college groups have nearly identical fractions of import spending, and the same holds true for imports from China. We will use the combined estimates in the model calibrations below.

6 Differences in Exposure to the Labor Market Effects of Trade

Moving from the expenditure side to the earnings side, this section reports reduced-form evidence characterizing the extent to which different education groups are exposed to the labor market effects of trade. As discussed in Section 2, the earnings channel of trade liberalization can affect labor demand through

intensified import competition, increased opportunities to export, cheaper intermediate inputs, as well as through income effects due to the gains from trade. This section documents the exposure of the two education groups to these forces. Differences in exposure we find imply that the earnings channel should favor college graduates. Our main analysis is based on industry-level data, in parallel with Section 3, but we discuss possible aggregation biases at the end of the section.

6.1 Data

Payroll data by industry and education group is the first ingredient we need to compute labor market exposure to trade for each group of workers. We rely on the 2007 American Community Survey (ACS) and the 2007 Quarterly Survey of Employment and Wages (QCEW) to obtain this information.³¹ Specifically, we aggregate individual-level data in the ACS to compute the payroll share of college-educated workers in each private industry. Since the industry classification in the ACS is not sufficiently detailed (253 industries), we infer the college payroll share at a finer level of disaggregation based on the fact that skill intensity is strongly correlated with average wages across industries, and average wages are available for each detailed industry from the 2007 QCEW. Data Appendix B.6 describes the imputation procedure. Multiplying the total industry payroll from QCEW by the imputed skill intensity, we obtain payroll estimates by detailed industry and education.

We then compute four industry-level outcomes: import penetration rates, export shares, the share of imported inputs, and income elasticities. For the first three outcomes, we use industry-level data as in Section 3. To estimate income elasticities, we use the CEX (Econometric Appendix C.2 describes the procedure).

6.2 Results and Mechanisms

The reduced-form patterns indicate that the earnings channel should favor college graduates. Table 6 reports the average and differential exposure of education groups to the various labor market effects of trade. In line with the model, payroll weights are used for all statistics.

First, we find that college graduates are less exposed to import competition. Column (1) of Table 6 reports that the average import penetration in domestic industries is only 3.97%. This share is low, for instance in comparison to the imports-to-GDP ratio, because international specialization limits the negative impact of import competition on industry size (e.g., Wood 1995): employment and payroll are low in industries in which the U.S. has largely stopped producing, such as toys. While consumption-side gains coming from an industry are scaled by *expenditures* in that industry, the reduction in labor demand due to import competition is scaled by the industry's *payroll*. The following rows of Column (1) establish that industries that employ college graduates are less exposed to import competition: average import

³¹The ACS is the long form of the population census that is answered by a random 1% sample of the U.S. population every year. We obtain the 2007 ACS via IPUMS (Ruggles et al. 2015). The QCEW tabulations are published by the Bureau of Labor Statistics based on unemployment insurance statistics.

penetration is 3.91% for workers with a college degree, compared with 4.03% for those without. Albeit small, the 0.13 p.p. difference is statistically significant.³²

The lower exposure of college graduates to import competition is interesting to investigate in the context of standard trade theories, as it may appear consistent with a standard Hecksher-Ohlin mechanism. Since the U.S. is a relatively skill-abundant country, its imports may be expected to be higher in low skill-intensive industries. However, this Hecksher-Ohlin interpretation of the data is largely misguided, as can be seen by decomposing the differential exposure to import competition into the components “between” and “within” goods and services. The lower exposure of college graduates to import competition is driven by the fact that services constitute a larger share of their payroll and are much less imported than goods. Within sectors, college graduates are in fact more exposed to import competition, in contrast with the standard Hecksher-Ohlin prediction. Online Appendix Table A8 reports that services constitute 88.7% (82.0%) of payroll for workers with (without) a college degree. The average import penetration is 23.9% for goods and 0.55% for services. If the two groups had identical compositions of payroll within goods and within services, import competition exposure for college graduates would have been 1.56 p.p. smaller than for workers without a college degree, which is a much bigger difference than what we observe in the data.

The finding that more skill-intensive industries have *higher* import penetration within goods and within services is easy to see graphically. Panel (a) of Figure 8 plots import penetration against college payroll share across industry bins (each bin represents 5% of the data) and shows that the positive slopes are robust and not driven by outliers. The slope is quite large for goods and small for services.

To identify the parts of the product space contributing to within-sector differences in exposure to import competition, Panel (b) of Figure 8 groups industries by subsectors. The size of each circle reflects the importance of each subsector according to its share in total payroll. Like on the expenditure side, “Food” and “Computers and electronics” are characteristic subsectors within the goods sector: while food manufacturing is low-skill intensive and does not have much import competition, electronics is high-skill intensive and has a high share of imports. The last rows of Column (1) of Table 6 show that the within-sector difference in import competition between education groups mainly occurs across subsectors, which implies that Panel (b) of Figure 8 is an accurate depiction of the main forces at play in the data.

Robustness Appendix D.3 shows that the positive relationship between import penetration and skill intensity among the goods-producing sector is a relatively recent phenomenon. Using the NBER CES panel data on manufacturing industries, we establish that this relationship was flat in 1992, weakly increasing in 1999, but became steep by 2007 (Figure A7). Growing imports of machinery and electronics explain why the slope increases over time.

In addition to direct import competition in the industry of a worker’s employment, import competition in downstream industries also affects labor demand and thus wages, potentially differently across education

³²Similar to Section 3, inference here is based on the randomness of the ACS sample. As it is a very large sample (1% of U.S. population), standard errors are small. Errors in the industry import penetration and other outcomes are non-statistical (e.g. due to the imperfect measurement of imports in the I-O table) and are not taken into account.

groups. Column (2) of Table 6 takes this into account by using the I-O adjusted import penetration as the outcome variable. This adjustment is performed using the input-output table, adding import penetration rates in downstream industries.³³ The differential exposure to import competition increases by a factor of six, from -0.13 to -0.79 p.p., primarily due to the increase in the between-sector component. Intermediate goods-producing industries mostly sell to other industries in the goods sector, therefore they suffer more from import competition. As a result, low-skilled workers employed in this sector suffer relatively more from additional import competition. In contrast, the magnitude of the within-sector component is not affected very much by I-O linkages: within each sector, workers with and without a college degree have a similar propensity to work for industries that supply other industries that are competing with the rest of the world.

We obtain qualitatively similar patterns when considering import competition with specific trading partners. In online Appendix Table A9 we report the differential exposure to import competition with China, NAFTA, and developed economies separately. The general finding that college graduates are less exposed to the adverse labor market effects of trade holds for each of these specific trading partners. The between-sector force is generally the most important channel and, in the cases of China and developed economies, it is partially offset by the positive relationship between import penetration and skill intensity within goods.³⁴

The remaining columns of Table 6 conduct a similar analysis for export shares, imported inputs and income elasticities. In all cases, results are reported both with and without the adjustment for input-output linkages. It turns out that I-O linkages do not make any qualitative difference, therefore we only discuss the I-O adjusted patterns.

We find that the export channel favors college graduates. Column (4) of Table 6 shows that an average industry (weighted by payroll) exports 9.39% of its output, with equal proportion of direct and indirect exports. The exposure of college graduates to exporting opportunities is very slightly higher. As previously, there are offsetting effects. The between-sector force favors workers without a college degree because goods are more exported, but within sectors workers with a college degree are more likely to work for industries that export more, which happens to more than offset the between-sector force. As illustrated by Panel (a) of Figure 9, “Computer and electronics” are more skill intensive and export more compared with “Food.” Similarly for services, “Professional and business services” and “Finance” are more skill intensive and export more in comparison with “Construction” or “Accommodation and food.”

Next, we show that college graduates benefit less from imported inputs. According to Column (6), this pattern is due to both between- and within-sector differences in the use of intermediate inputs. For

³³Note that the I-O adjusted import penetration that we analyze here is different from the total import content of the industry from Section 3. We are now adding up import penetration in downstream (buying) industries, as demand shocks propagate upward from those industries. Conversely, on the expenditure side we were adding up imports from upstream (supplying) industries, as price shocks propagate downward from those industries (see, for example, Acemoglu et al. 2016a for a discussion of these effects).

³⁴Online Appendix Figure A8 depicts the contributions of subsectors to these patterns. One caveat is that data limitations do not allow us to decompose imports of services by country, so we assume that they are zero. This may bias the findings, but the bias is unlikely to be large for China, which accounts for a small share of U.S. services imports.

instance, within services, “Construction” and “Transportation” are the subsectors with the highest shares of imported inputs, and both of them have low skill intensity. The contributions of different subsectors to differential exposure to imported inputs is shown in Panel (b) of Figure 9.

Finally, we find that college graduates work in industries with higher income elasticities. The average income elasticity weighted by the college payroll is 1.13, relative to 1.02 when payroll of non-college workers is used. This finding is consistent with prior research (Caron et al. 2014; Leonardi 2015) and implies that the income effects of trade favor college graduates (Caron et al. 2017; He 2018). As indicated by Panel (c) of Figure 9, the difference in income elasticities across education groups in our data is largely driven by the “Education” subsector, which is highly income-elastic and skill-intensive.

In sum, we find that college graduates are employed in industries with lower import penetration, higher export shares, and higher income elasticities, which in our model implies that trade liberalization should favor this group of workers in the labor market. They also work for industries with lower fractions of imported inputs, generating a counteracting force.

6.3 Robustness

The various patterns documented in this section are based on industry-level data and may therefore suffer from aggregation bias. In Robustness Appendix D.3, we conduct two additional analyses to address this potential issue.

First, we use the plant-level microdata from the Census of Manufactures and the Management and Organizational Practices Survey (MOPS) to compare the differences in exposure to exports between education groups, as well as between non-production and production workers. We find that more skill-intensive plants within the same industry tend to export more; however, the main difference is across manufacturing industries and the degree of aggregation bias is small (Table A10).

Second, on the import side, we do not know which workers within industries are particularly vulnerable to import competition. Building on Borjas et al. (1997), a plausible proxy for the skill level of the marginal worker displaced by import competition may be the skill intensity of the U.S. industry in the past. In the extension of our model developed in Theory Appendix A.3, we assume that each industry has two segments: one is affected by import competition while the other is insulated from it. Skill intensity in the import-competing segment is proxied for using the data from the 2000 and 1990 population censuses. We find that the differential exposure to imports is substantially larger under this set of assumptions, but still not sufficient to generate large changes in the counterfactuals to which we turn in the next section.

Besides investigating aggregation issues, in the online Appendix we apply our reduced-form methodology to investigate whether capital owners are differentially exposed to the earnings effects of trade compared to workers. The patterns are reported in online Appendix Table A11 and discussed in Robustness Appendix D.4; they show that exposure is similar for workers and capital owners across all four margins: import competition, exports, intermediate inputs and income elasticities.

7 Estimates of the Distributional Effects of Trade Policies

The previous sections have documented that the share of spending on imports is similar for college and non-college educated consumers, while college graduates are relatively less exposed to the negative labor market effects of trade through most channels. Qualitatively, these patterns predict that trade policies should favor college graduates. However, reduced-form statistics are not sufficient to quantify the counterfactual effects of trade liberalizations, in particular for the earnings channel, for two main reasons. First, the magnitude of the earnings channel depends on structural parameters of the model—elasticities of substitution in demand and production. Second, the reduced-form patterns do not capture general equilibrium effects which, in the model, result from endogenous changes in domestic wages that affect prices and demand.

To quantify the average and distributional welfare gains of trade policies, this section uses the model from Section 2, calibrated with the reduced-form estimates from previous sections as well as structural elasticities borrowed from the literature. We decompose the distributional effects into the expenditure and earnings channels, and further into different mechanisms to provide evidence on their relative importance. We focus on two specific trade policies: a bilateral reduction in all import and export barriers and a fall in barriers on Chinese imports. In both cases we consider a 10% change in trade costs to ease exposition; as all results are based on the first-order approximation, they scale proportionately to the magnitude of the shock. Our calibration is at the industry level, structured around the detailed input-output table, although we incorporate the results from Sections 4 and 5 as well. We find that college graduates benefit from trade liberalization 25% more than non-college graduates; this difference is primarily driven by the earnings channel and slightly strengthened by the expenditure channel. The pro-skilled bias is moderately stronger in the case of China.

7.1 Elasticities

Demand Elasticities. Besides income elasticities estimated in Section 6, the non-homothetic nested CES demand system (equation (1)) is characterized by elasticities of substitution at each nesting tier: ξ_j between domestic and foreign varieties in industry j , ε_r between I-O industries within goods and services sectors, and ρ between goods and services. We take typical values from the literature and check robustness of the results to a range of their values.

For substitution between domestic and foreign varieties, our baseline calibration assumes that this elasticity is 3.5 in all industries (which is equivalent to the trade elasticity of 2.5 for trade flows measured by value rather than quantity). The value we use is near the median elasticity of 3.7 reported in Broda and Weinstein (2006) for ten-digit industries, and of 3.4–3.7 in Soderbery (2015) using the same Broda-Weinstein method but for eight-digit industries and for different years of data, as well as near the mean of 3.6 in Ossa (2015). In robustness checks, we consider values of ξ_j between 1.9 and 5.1, which correspond to the estimates from Soderbery (2015)’s LIML procedure and Simonovska and Waugh (2014). This interval also covers typical values of the elasticity of substitution between domestic and foreign varieties

in Feenstra et al. (2018). We also allow ξ_j to vary across 3-digit I-O industries according to the estimates from Broda and Weinstein (2006).³⁵

Estimates of the elasticities of substitution between sectors (goods and services) and industries (IO6) are also required. There is substantial debate on the value of the elasticity of substitution between goods and services, but it is generally recognized that the two sectors are complements, i.e. $\rho < 1$. We follow the recent paper by Cravino and Sotelo (2018) and set $\rho = 0.2$ in our baseline calibration, but also consider a range of other values between zero and one for robustness.

Regarding the elasticities of substitution between industries within each sector, ε_r , we follow the prevalent approach in the literature and set the elasticity to one (Dawkins et al. 2001; Costinot and Rodríguez-Clare 2015). In a robustness exercise, consider a range of $\varepsilon_r \in [0.8, 3.5]$ since this elasticity is likely to be above ρ and below ξ_j .³⁶

Macro Elasticity of Substitution between Labor Types. On the production side, the elasticities of substitution between skilled and unskilled labor in each industry enter only through the macro elasticity σ_{macro} . We follow Burstein and Vogel (2017), Cravino and Sotelo (2018), and Caron et al. (2017) by calibrating the macro elasticity directly rather than aggregating it from micro estimates. We use an estimate of 1.41 for the baseline calibration obtained by Katz and Murphy (1992). We also check robustness to the range of [1.41, 1.8], with the upper bound corresponding to the estimates from Acemoglu (2002) and Acemoglu and Autor (2011).

7.2 Results and Mechanisms

Overview. We find that trade liberalizations generate a modest increase in inequality through the earnings channel, while the expenditure channel is close to neutral. Table 7 presents the key results of our baseline model calibration for a 10% bilateral reduction trade barriers and for a 10% reduction in barriers on Chinese imports in columns (1) and (2), respectively.

A bilateral liberalization creates welfare gains of 1.71% on average, as indicated by the first line of Table 7. However, these gains are unequal, at 1.90% for college graduates and 1.52% for those without a college degree. The pro-skilled difference of 0.379 p.p. constitutes 22.2% of the average gain (or 25.0% relative to the gains of the unskilled) and is mostly driven by the earnings channel (0.352 p.p.); the expenditure channel strengthens the pro-skilled bias by 0.027 p.p. only. The expenditure channel here is a combination of across-industry differences in import spending from Section 3 and within-industry differences from Sections 4–5.

³⁵We convert 10-digit HS codes to NAICS and then to 3-digit I-O and take the median of the Broda and Weinstein (2006) elasticities within each group. To further reduce estimation noise, we repeat this procedure for the Soderbery (2015) estimates that use the same Broda-Weinstein methodology on a different sample, and average the results.

³⁶A recent paper by Redding and Weinstein (2017) estimated the elasticities of substitution between 6- and 4-digit NAICS industries to be 1.47 and 1.34, respectively. The estimate by Hottman and Monarch (2018) using 4-digit HS industries is 2.78. The range of elasticities we use covers all of these values, although they are not directly comparable, for instance because they only use import data.

A reduction of import barriers with China has much smaller average gains of 0.153%, both because this shock affects only one country and because barriers are reduced only on the import side. These gains are also biased towards the skilled, with gains of 0.189% compared with 0.119% for the unskilled. Expressed as a percentage of the average gain, the difference is larger (45.5%); it is again driven by the earnings channel and slightly strengthened by the expenditure channel.

The remainder of this section decomposes the average gains and the distributional effects into different mechanisms. Following the logic of the model, we first explain how the average gains are shaped by the average share of import spending and general equilibrium effects related to endogenous wages. We proceed to a similar analysis for the expenditure channel. Finally, we analyze the earnings channel, decomposing it into the mechanisms related to exporting, import competition, imported intermediate inputs, income and substitution effects, as well as general equilibrium forces.

Average Gains. We estimate the average welfare gain from a 10% bilateral liberalization at 1.71%. The main component of this estimate is the direct effect of falling import prices. As the average share of imports in expenditures estimated in Section 3 equals 12.6%, this generates a 1.26% average welfare gain. This number is adjusted by the equilibrium responses of the average wage and the skill premium, as in equation (7).³⁷ We find that the average wage, which is proportional to GDP, grows by 3.55% relative to the foreign numeraire, providing an additional source of welfare gains through the terms of trade.³⁸ The adjustment due to the changing skill premium is minimal.

The same logic applies when considering a fall of imports barriers for products from China. After this shock, the domestic economy shrinks because of import competition, so the average wage falls by 0.32%. This reduces the total welfare gain from 0.193% (corresponding to the 1.93% average import spending on imports from China in Table 2) to 0.153%.

Expenditure Channel. According to equation (8), the expenditure channel is primarily driven by the difference in import spending between skill groups, through both a direct effect on import prices and the growth of domestic wages, which also makes imports more affordable. We compute the difference in import spending across groups as a combination of the across-industry difference from Section 3 and the within-industry differences from Sections 4–5; Data Appendix B.5 describes the procedure. A slightly larger share of imports for college graduates implies that their gains from the bilateral liberalization are 2.8 basis points (0.028 p.p.) higher.

Besides the difference in import spending, equation (8) includes an additional “segregation” force that operates if the skill premium changes and the consumption baskets of the two groups differ in terms of skill intensity. This force turns out to be quantitatively negligible.

³⁷All estimates in this section use the general model with input-output linkages developed in Theory Appendix A.2. We provide references to the analogous equations from the simplified model in the main text.

³⁸GDP grows because a reduction in export barriers allows exporting industries to grow, whereas the effect of import barriers is twofold: import competition reduces domestic income, but cheaper intermediate inputs increase it. These changes are further magnified by the multiplier effect (equation (14)), estimated at 2.41.

For the China shock, falling import prices generate a 0.80 b.p. pro-skilled benefit but general equilibrium forces weaken it by a small 0.08 b.p. because the average wage is falling, making *all* (not just Chinese) imports less affordable. In both cases, the expenditure channel favor college graduates but is very small in magnitude.

Earnings Channel. We find that the earnings channel benefits college graduates relatively more. Considering a bilateral trade liberalization, Table 7 shows that additional gains for college workers through the earnings channel are equal to 20.6% of the average gain (or 35.2 basis points of real income after a 10% liberalization). This section quantifies different mechanisms that contribute to this overall distributional effect.

The distributional effects from the earnings channel stem from six forces. The decomposition in Panel (a) of Figure 10 is guided by the results of Section 2.2 (Step 2) and shows the four forces that we investigated in the reduced form in Section 6 together with substitution effects and general equilibrium effects. As predicted, intensified import competition, growing exporting opportunities, and income effects are all pro-skilled. Quantification shows that their contributions equal to 6.31%, 2.44%, and 6.13% of the average welfare gain, respectively. Since college graduates work in industries that use fewer imported inputs, cheaper imported inputs generate a mild offsetting force, equal to -4.04% of the average welfare gain. Substitution effects, which we have not explored in the reduced-form analysis, are also pro-skilled, at 5.93% of the average gain. The reason, as pointed out by Cravino and Sotelo (2018), is that complementarity between goods and services reallocates production towards services, which are more skill-intensive. The other type of substitution effects, which is due to reallocation between industries within each sector, is mechanically shut down in our baseline calibration, as the corresponding elasticity of substitution is set to one. Finally, general equilibrium forces caused by the rising average wage generate an additional pro-skilled effect, equal to 3.87% of the average gain.

The finding that the import competition force is relatively small is interesting in the context of the trade literature. In the traditional two-sector, two-factor formulation of the Heckscher-Ohlin model, the “gains” from trade for non-college graduates have to be negative. Instead, we find that the gains from trade for this skill group are positive and that import competition makes their gains lower by only 6.31% relative to the average gains. The reason mirrors our discussion of the differential exposure to import competition in Section 6.2—offsetting forces between and within goods and services. After a trade liberalization, demand is reallocated from domestic goods to domestic services, which do not suffer from import competition as much. At the same time, within sectors demand is also reallocated toward industries such as food—those with low import penetration and, on average, low skill intensity. Applying the within-between decomposition to the import competition effect ($\Delta_{VA} \left[\eta_{jc}^{\text{import}} \right] / \sigma_{\text{macro}}$), we find that, absent the within-sectoral offsetting pattern, import competition effects would have been larger, around 15.5% of the average gains.

Considering a fall of import barriers with China (with no shock to export barriers), the earnings channel is also pro-skilled and larger in magnitude. The pro-skilled earnings channel is 40.8% of the

average welfare gain, which amounts to 6.3 basis points of real income after a 10% trade barrier reduction. Panel (b) of Figure 10 shows that this pattern is driven by import competition (23.0% of the average gain), substitution and income effects (14.6% and 10.1%), while the effects of cheaper imported inputs and general equilibrium wage decline are biased against the skilled (-2.9% and -3.8%, respectively).

7.3 Robustness and Extensions

Sensitivity to Choice of Elasticities. The earnings channel depends on a number of elasticities: the elasticity of substitution between goods and services (ρ), the elasticity of substitution between industries within sectors (ε), the trade elasticity (ξ), and the aggregate elasticity of substitution between skilled and unskilled labor (σ_{macro}); there is substantial uncertainty about their values. To investigate whether our results are sensitive to the choice of these parameters, we repeat the calibration under the range of elasticity values mentioned in Section 7.1 on the basis of the literature. We examine the sensitivity of the results varying one elasticity at a time and keeping the other elasticities to their baseline values.

Across the relevant range of elasticities, the upper and lower bounds for the distributional effects from the earnings channel are reported in Panel (b) of Table 7. Due to the log-linearization approach, the distributional effects vary monotonically with the elasticities and the upper and lower bounds are reached for the extreme values of the range of elasticities we consider.³⁹ Across all parameter values, the earnings channel is always pro-skilled, much larger than our estimate of the distributional effect from the expenditure channel reported in Panel (a), and much smaller than would be necessary to make the unskilled group lose from trade. The earnings channel ranges between 12.8% and 23.6% of the average gains in the case of a uniform trade liberalization, and between 29.3% and 55.7% for the shock to Chinese imports. These results lend support to the robustness of the main calibration results from Panel (a).

Counterfactuals Based on Observed Trade Shocks. Our analysis so far has focused on the distributional effects from a uniform decrease in trade barriers. We have also considered three other counterfactuals, inspired by observed changes in trade policy and trade costs in recent years. We investigated the impact of the removal of 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 between 1992 and 2007, and the observed change in transportation and insurance costs (“import charges”) during the same period. The methodology is similar to our baseline calibration and is fully described in Robustness Appendix D.5.

The results are reported in Online Appendix Table A12. Across all three counterfactuals, the expenditure channel is relatively small. The earnings channel is in favor of college graduates in all three cases, but its magnitude differs markedly across counterfactuals: it is quite strong for the removal of the Trump import tariffs, while it is modest for the change in tariffs duties and negligible for the change in import

³⁹Technically speaking, the denominator—average welfare gains—also varies with elasticities due to general equilibrium effects (equation (7)). However, we verify that variation in average gains is very small across all robustness checks (between 1.65 and 1.72% of consumption), so this does not affect the results.

charges. Robustness Appendix D.5 provides further details.

Trade Liberalizations with NAFTA and Developed Economies. To conclude this section, online Appendix Table A13 reports the distributional effects of a 10% reduction in all trade barriers on imports from either NAFTA or developed economies. In both cases, the welfare gains are moderately larger for college graduates. For NAFTA, the earnings channel favors college graduates and is partly offset by the expenditure channel. For developed economies, the earnings and expenditure channels both favor college graduates.

8 Conclusion

This paper has characterized the distributional effects of trade in the United States, taking into account both changes in consumer prices (*expenditure channel*) and in wages (*earnings channel*). Combining theory and empirics in a transparent way, we established three results.

First, on the expenditure side, we documented that spending shares on imports, either directly or via imported inputs embedded in domestic goods, are very similar across education and income groups. They are slightly higher for more educated and richer consumers. This pattern does not result from the fact that households in different education or income groups purchase similar consumption bundles. Rather, a number of forces across and within sectors offset each other: college graduates spend relatively more on (largely non-traded) services but within tradables they spend more on imports (e.g., they spend relatively more on electronics than on food, and they tend to purchase more imported cars, SUVs and imported brands of consumer packaged goods than less-educated consumers).

Second, we established a series of reduced-form patterns governing the distributional effects of trade via wages. Three forces contribute to an increase in the college wage premium: college-educated workers are employed in industries that are less exposed to import competition, that export more, and that are more income-elastic. However, we also found a force operating in the other direction: college-educated workers are employed in industries that rely less on imported inputs.

Third, we combined and assessed the quantitative importance of the reduced-form findings using a quantitative trade model, taking into account general equilibrium effects. We found that the expenditure channel is distributionally neutral, while the earnings channel implies that the gains from a uniform trade liberalization (applying to all trading partners) are 25% larger for individuals with a college degree, compared to those without. The expenditure channel remains close to neutral in a range of counterfactuals, such as a uniform change in tariffs on imports from China and changes in trade policy recently implemented in the United States; the earnings channel favors college graduates in all of the cases.

Although these results are specific to the United States and to the period under consideration, the method and tools we employed can be readily applied in other contexts, for instance to investigate the distributional impacts of other major changes in trade policy such as Brexit.

References

- Acemoglu, Daron.** 2002. “Technical Change, Inequality, and the Labor Market.” *Journal of Economic Literature* 40:7–72.
- Acemoglu, Daron, Ufuk Akcigit, and William R. Kerr.** 2016a. “Networks and the Macroeconomy: An Empirical Exploration.” In *NBER Macro Annual 2015*, edited by Martin Eichenbaum and Jonathan Parker.
- Acemoglu, Daron, and David H. Autor.** 2011. “Skills, tasks and technologies: Implications for employment and earnings.” In *Handbook of Labor Economics*, 4:1043–1171. Elsevier B.V.
- Acemoglu, Daron, David H. Autor, David Dorn, Gordon H. Hanson, and Brendard Price.** 2016b. “Import Competition and the Great U.S. Employment Sag of the 2000s.” *Journal of Labor Economics* 34:S141–S198.
- Aguiar, Mark, and Mark Bils.** 2015. “Has Consumption Inequality Mirrored Income Inequality?” *American Economic Review* 105:2725–2756.
- Amiti, Mary, Mi Dai, Robert C. Feenstra, and John Romalis.** 2018a. “How Did China’s WTO Entry Benefit U.S. Consumers?” *Working Paper*.
- Amiti, Mary, Oleg Itskhoki, and Jozef Konings.** 2018b. “International Shocks, Variable Markups and Domestic Prices.” *Working Paper*.
- Antoniades, Alexis, and Nicola Zaniboni.** 2016. “Exchange Rate Pass-Through into Retail Prices.” *International Economic Review* 57:1425–1447.
- Arkolakis, Costas, Arnaud Costinot, Dave Donaldson, and Andrés Rodríguez-Clare.** 2017. “The elusive pro-competitive effects of trade.” *NBER Working Paper*.
- Armington, Paul S.** 1969. “A Theory of Demand for Products Distinguished by Place of Production.” *IMF Staff Papers* 16:159–178.
- Artuç, Erhan, Shubham Chaudhuri, and John McLaren.** 2010. “Trade shocks and labor adjustment: A structural empirical approach.” *American Economic Review* 100:1008–1045.
- Autor, David H., David Dorn, and Gordon H. Hanson.** 2013. “The China Syndrome: Local Labor Market Impacts of Import Competition in the United States.” *American Economic Review* 103:2121–2168.
- Autor, David H., David Dorn, Gordon H. Hanson, and Jae Song.** 2014. “Trade Adjustment: Worker-Level Evidence.” *The Quarterly Journal of Economics* 129:1799–1860.
- Bai, Liang, and Sebastian Stumpner.** 2018. “Estimating US Consumer Gains from Chinese Imports.” *Working Paper*.
- Bems, Rudolfs, and Julian Giovanni.** 2016. “Income-Induced Expenditure Switching.” *American Economic Review* 106:3898–3931.
- Berman, Eli, John Bound, and Zvi Griliches.** 1994. “Changes in the Demand for Skilled Labor Within U. S. Manufacturing: Evidence From the Annual Survey of Manufactures.” *The Quarterly Journal of Economics* 109:367–397.

- Bernard, Andrew B., J. Bradford Jensen, and Peter K. Schott.** 2006. “Survival of the best fit: Exposure to low-wage countries and the (uneven) growth of U.S. manufacturing plants.” *Journal of International Economics* 68:219–237.
- Boppart, Timo.** 2014. “Structural Change and the Kaldor Facts in a Growth Model With Relative Price Effects and Non-Gorman Preferences.” *Econometrica* 82:2167–2196.
- Borjas, George J., Richard B. Freeman, and Lawrence F. Katz.** 1997. “How Much Do Immigration and Trade Affect Labor Market Outcomes?” *Brookings Papers on Economic Activity*.
- Breinlich, Holger, Elsa Leromain, Dennis Novy, and Thomas Sampson.** 2017. “The Brexit Vote and Inflation.” *CEP Discussion Paper*.
- Broda, Christian, and David E. Weinstein.** 2006. “Globalization and the Gains From Variety.” *The Quarterly Journal of Economics* 121:541–585.
- . 2010. “Product Creation and Destruction: Evidence and Price Implications.” *American Economic Review* 100:691–723.
- Burstein, Ariel, and Jonathan Vogel.** 2017. “International Trade, Technology, and the Skill Premium.” *Journal of Political Economy* 125:1356–1412.
- Caliendo, Lorenzo, Maximiliano Dvorkin, and Fernando Parro.** 2018. “Trade and Labor Market Dynamics: General Equilibrium Analysis of the China Trade Shock.” *Working Paper*.
- Caliendo, Lorenzo, and Fernando Parro.** 2015. “Estimates of the trade and welfare effects of NAFTA.” *Review of Economic Studies* 82:1–44.
- Caron, Justin, Thibault Fally, and James R. Markusen.** 2014. “International trade puzzles: A solution linking production and preferences.” *Quarterly Journal of Economics* 129:1501–1552.
- . 2017. “Per Capita Income and the Demand for Skills.” *Working Paper*.
- Chaney, Thomas.** 2008. “Distorted Gravity: The Intensive and Extensive Margins of International Trade.” *American Economic Review* 98 (August): 1707–1721.
- Chodorow-Reich, Gabriel.** 2018. “Geographic Cross-Sectional Fiscal Spending Multipliers: What Have We Learned?” *Working Paper*.
- Comin, Diego, Danial Lashkari, and Martí Mestieri.** 2016. “Structural Change with Long-run Income and Price Effects.” *Working Paper*.
- Costinot, Arnaud, and Andrés Rodríguez-Clare.** 2015. *Trade Theory with Numbers: Quantifying the Consequences of Globalization*, 4:197–261.
- Cravino, Javier, and Andrei A. Levchenko.** 2017. “The distributional consequences of large devaluations.” *American Economic Review* 107:3477–3509.
- Cravino, Javier, and Sebastian Sotelo.** 2018. “Trade Induced Structural Change and the Skill Premium.” *Working Paper*.
- Dawkins, Christina, T. N. Srinivasan, and John Whalley.** 2001. “Calibration.” *Handbook of Econometrics* 5:3653–3703.

- De Loecker, Jan, Pinelopi K. Goldberg, Amit K. Khandelwal, and Nina Pavcnik.** 2016. “Prices, Markups, and Trade Reform.” *Econometrica* 84:445–510.
- De Loecker, Jan, and Frederic Warzynski.** 2012. “Markups and Firm-Level Export Status.” *American Economic Review* 102:2437–2471.
- Deaton, Angus.** 1989. “Rice Prices and Income Distribution in Thailand: A Non-Parametric Analysis.” *The Economic Journal* 99:1–37.
- Dekle, Robert, Jonathan Eaton, and Samuel Kortum.** 2008. “Global Rebalancing with Gravity: Measuring the Burden of Adjustment.” *IMF Staff Papers* 55:511–540.
- Dhingra, Swati, Hanwei Huang, Gianmarco I. P. Ottaviano, Joao Paulo Pessoa, Thomas Sampson, and John Van Reenen.** 2017. “The Costs and Benefits of Leaving the EU: Trade Effects.” *CEP Discussion Paper 1478*.
- Eaton, Jonathan, and Samuel Kortum.** 2002. “Technology, geography, and trade.” *Econometrica* 70:1741–1779.
- Faber, Benjamin.** 2014. “Trade Liberalization, the Price of Quality, and Inequality: Evidence from Mexican Store Prices.” *Working Paper*.
- Fajgelbaum, Pablo, Gene M. Grossman, and Elhanan Helpman.** 2011. “Income Distribution , Product Quality , and International Trade.” *The Journal of Political Economy* 119:721–765.
- Fajgelbaum, Pablo, and Amit K. Khandelwal.** 2016. “Measuring the Unequal Gains from Trade.” *Quarterly Journal of Economics* 131:1113–1180.
- Feenstra, Robert C., and Gordon H. Hanson.** 1996. “Globalization, Outsourcing, and Wage Inequality.” *American Economic Review: Papers & Proceedings* 86:240–245.
- Feenstra, Robert C., Philip Luck, Maurice Obsteld, and Katheryn N. Russ.** 2018. “In Search of the Armington Elasticity.” *Review of Economics and Statistics* 100:135–150.
- Felbermayr, Gabriel, Benjamin Jung, and Mario Larch.** 2015. “The welfare consequences of import tariffs: A quantitative perspective.” *Journal of International Economics* 97:295–309.
- Finger, J. M.** 1976. “Trade and Domestic Effects of the Offshore Assembly Provision in the U.S. Tariff.” *American Economic Review* 66:598–611.
- Furman, Jason, Katheryn Russ, Jay Shambaugh, and Jason Furman.** 2017. “US tariffs are an arbitrary and regressive tax.” *VOX CEPR’s Policy Portal*.
- Gabaix, Xavier.** 2011. “The Granular Origins of Aggregate Fluctuations.” *Econometrica* 79:733–772.
- Gailes, Arthur, Tamara Gurevich, Serge Shikher, and Marinos Tsigas.** 2018. “Gender and Income Inequality in United States Tariff Burden.” *Working Paper*.
- Garner, Thesia I., Robert McClelland, and William Passero.** 2009. “Strengths and Weaknesses of the Consumer Expenditure Survey from a BLS Perspective.” *Working Paper*.
- Goos, Maarten, Alan Manning, and Anna Salomons.** 2014. “Explaining Job Polarization: Routinization and Offshoring.” *American Economic Review* 104:1–20.

- Grossman, Gene M., and Esteban Rossi-Hansberg.** 2008. "Trading tasks: a simple theory of offshoring." *American Economic Review* 98:1978–1997.
- Hanoch, Giora.** 1975. "Production and Demand Models with Direct or Indirect Implicit Additivity." *Econometrica* 43:395–419.
- He, Zheli.** 2018. "Trade and Real Wages of the Rich and Poor : Cross-Country Evidence." *Working Paper*.
- Hottman, Colin J, and Ryan Monarch.** 2018. "Estimating Unequal Gains across U.S. Consumers with Supplier Trade Data." *Working Paper*.
- Jaravel, Xavier.** 2018. "The Unequal Gains from Product Innovations: Evidences from the US Retail Sector." *Working Paper*.
- Jaravel, Xavier, and Erick Sager.** 2018. "What are the Price Effects of Trade ? Evidence from the U.S. and Implications for Quantitative Trade Models." *Working Paper*.
- Jones, Ronald W.** 1965. "The Structure of Simple General Equilibrium Models." *Journal of Political Economy* 73:557.
- Kaplan, Greg, and Sam Schulhofer-Wohl.** 2017. "Inflation at the household level." *Journal of Monetary Economics* 91:19–38.
- Katz, Lawrence F., and Kevin M. Murphy.** 1992. "Changes in Relative Wages, 1963-1987 - Supply and Demand Factors." *Quarterly Journal of Economics* 107:35–78.
- Krugman, Paul.** 1980. "Scale Economies, Product Differentiation, and the Pattern of Trade." *The American Economic Review* 70:950–959.
- . 2000. "Technology, trade and factor prices." *Journal of International Economics* 50:51–71.
- . 2008. "Trade and Wages, Reconsidered." *Brookings Papers on Economic Activity*: 103–154.
- Kucheryavyy, Konstantin, Gary Lyn, and Andrés Rodríguez-clare.** 2018. "Grounded by Gravity: A Well-Behaved Trade Model with Industry-Level Economies of Scale."
- Lawrence, Robert Z., and Matthew J. Slaughter.** 1993. "International Trade and American Wages in the 1980s: Giant Sucking Sound or Small Hiccup?" *Brookings Papers: Microeconomics*: 161–226.
- Lebow, David E., and Jeremy B. Rudd.** 2003. "Measurement Error in the Consumer Price Index: Where Do We Stand?" *Journal of Economic Literature* 41:159–201.
- Leonardi, Marco.** 2015. "The Effect of Product Demand on Inequality: Evidence from the US and the UK." *American Economic Journal: Applied Economics* 7:221–247.
- Levell, Peter, Martin O’Connell, and Kate Smith.** 2017. "The exposure of households’ food spending to tariff changes and exchange rate movements and exchange rate movements." *IFS Briefing Note BN213*.
- Matsuyama, Kiminori.** 2017. "Engel’s Law in the Global Economy: Demand-Induced Patterns of Structural Change and Trade across Countries." *Working Paper*.
- Morrow, Peter M., and Daniel Trefler.** 2017. "Endowments, Skill-Biased Technology, and Factor Prices: A Unified Approach to Trade." *NBER Working Paper*.

- Nigai, Sergey.** 2016. “On Measuring the Welfare Gains from Trade Under Consumer Heterogeneity.” *The Economic Journal* 126:1193–1237.
- Oberfield, Ezra, and Devesh Raval.** 2014. “Micro Data and Macro Technology.” *Working Paper*.
- Ossa, Ralph.** 2015. “Why trade matters after all.” *The Journal of International Economics* 97:266–277.
- Pierce, Justin R., and Peter K. Schott.** 2012. “A Concordance Between Ten-Digit U.S. Harmonized System Codes and SIC/NAICS Product Classes and Industries.” *Journal of Economic and Social Measurement* 37:61–96.
- Pierce, Justin R., and Peter K. Schott.** 2016. “The Surprisingly Swift Decline of U.S. Manufacturing Employment.” *American Economic Review* 106:1632–1662.
- Porto, Guido G.** 2006. “Using survey data to assess the distributional effects of trade policy.” *Journal of International Economics* 70:140–160.
- Redding, Stephen J., and David E Weinstein.** 2017. “Aggregating from Micro to Macro Patterns of Trade.” *NBER Working Paper*.
- Ruggles, Steven, Katie Genadek, Ronald Goeken, Josiah Grover, and Matthew Sobek.** 2015. *Integrated Public Use Microdata Series: Version 6.0*. Minneapolis.
- Schott, Peter K.** 2008. “The relative sophistication of Chinese exports.” *Economic Policy* 23:6–49.
- Simonovska, Ina, and Michael E Waugh.** 2014. “The elasticity of trade : Estimates and evidence.” *Journal of International Economics* 92:34–50.
- Soderbery, Anson.** 2015. “Estimating import supply and demand elasticities : Analysis and implications.” *Journal of International Economics* 96:1–17.
- Stolper, Wolfgang F., and Paul A. Samuelson.** 1941. “Protection and Real Wages.” *The Review of Economic Studies* 9:58–73.
- Theil, Henri.** 1975. *Theory and measurement of consumer demand*. 349. Elsevier Science Publishing Co Inc.
- Traiberman, Sharon.** 2018. “Occupations and Import Competition: Evidence from Denmark.” *Working Paper*.
- Wood, Adrian.** 1995. “How Trade Hurt Unskilled Workers.” *Journal of Economic Perspectives* 9:57–80.

Table 1: Summary Statistics

	All goods and services <i>Section 3</i> (1)	Consumer packaged goods <i>Section 4</i> (2)	Cars and light trucks <i>Section 5</i> (3)
Product space	170 final industries	12,700 firm-years	45 brands
Timeframe	2007	2007, 2012	2009–2015
Spending share on imports, %	12.58	11.10	44.40
→ China	1.93	4.15	—
→ NAFTA	2.65	1.91	23.07
→ 34 developed economies	3.21	3.10	18.51
% of sales to college graduates	39.81	31.18	34.34
Source of consumption data	CEX	Nielsen	CEX
Source of import content	BEA I-O Table	Economic Census, LFTTD	Ward’s Automotive
Weighting scheme	I-O personal final consumption	$\sqrt{\text{firm sales}}$, Nielsen	Number of sold vehicles, CEX

Notes: This table reports summary statistics for the three consumption datasets used in the paper. Column (1) is based on the industry-level data from Section 3, Column (2) on the micro data for consumer packaged goods from Section 4, and Column (3) on the micro data for motor vehicles from Section 5.

Table 2: Spending on Imports by Education Group, Industry Data

	Imports by Trading Partners							
	All Countries		China		NAFTA		Developed Economies	
	Total (1)	Direct (2)	Total (3)	Direct (4)	Total (5)	Direct (6)	Total (7)	Direct (8)
All, %	12.58	6.89	1.93	1.48	2.65	0.99	3.21	2.09
College, %	12.22	6.77	2.01	1.55	2.51	0.95	3.05	1.96
Non-college, %	12.82	6.97	1.88	1.43	2.75	1.02	3.31	2.17
College minus non-college, p.p.	-0.60	-0.20	+0.13	+0.12	-0.24	-0.07	-0.25	-0.21
	(0.15)	(0.13)	(0.04)	(0.04)	(0.03)	(0.02)	(0.04)	(0.04)
<i>as % of avg. import spending</i>	<i>-4.79</i>	<i>-2.91</i>	<i>6.57</i>	<i>8.07</i>	<i>-9.07</i>	<i>-7.14</i>	<i>-7.94</i>	<i>-10.26</i>
→ Between goods and services	-1.02	-0.82	-0.21	-0.20	-0.22	-0.13	-0.30	-0.28
	(0.13)	(0.11)	(0.03)	(0.03)	(0.03)	(0.02)	(0.04)	(0.04)
→ Within goods and services	+0.42	+0.62	+0.33	+0.32	-0.02	+0.06	+0.05	+0.06
	(0.05)	(0.04)	(0.02)	(0.03)	(0.01)	(0.01)	(0.03)	(0.03)
→ Between subsectors	+0.31	+0.50	+0.37	+0.35	-0.03	+0.05	-0.02	-0.02
	(0.04)	(0.04)	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.01)
→ Within subsectors	+0.11	+0.12	-0.03	-0.03	+0.00	+0.01	+0.07	+0.08
	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)

Notes: This table estimates the fraction of imports in expenditure across education groups using the industry-level data from Section 3. Total import spending includes consumption of imported products (direct import spending in 170 industries with positive personal consumption expenditures) and imported intermediate inputs embedded in domestic products (indirect import spending, measured using the input-output linkages across 380 industries in the input-output table). The table reports the average and differential spending in the entire economy and decomposes the difference into the within- and between- components according to equation (A27). NAFTA stands for Canada and Mexico, whereas Developed Economies are OECD members (excluding NAFTA), Taiwan, and Singapore. Subsectors are shown in Table A2. Standard errors are shown in parentheses.

Table 3: Spending on Imports by Education Group, Merged Nielsen-Census Sample

	All Imports	Imports by Trading Partner		
		China	NAFTA	Developed Economies
	(1)	(2)	(3)	(4)
All, %	11.10	4.16	1.91	3.10
College, %	11.50	4.02	1.95	3.37
Non-college, %	10.91	4.20	1.86	2.82
College minus non-college, p.p.	+0.59	-0.18	+0.09	+0.55
	(0.12)	(0.07)	(0.04)	(0.06)
<i>as % of avg. import spending</i>	<i>5.35</i>	<i>-4.37</i>	<i>4.61</i>	<i>17.63</i>
→ Within industries	+0.48	-0.10	+0.06	+0.38
	(0.11)	(0.05)	(0.03)	(0.06)
<i>as % of avg. import spending</i>	<i>4.34</i>	<i>-2.44</i>	<i>3.20</i>	<i>12.27</i>
→ Within product modules	+0.28	-0.14	+0.03	+0.28
	(0.06)	(0.03)	(0.02)	(0.04)
<i>as % of avg. import spending</i>	<i>2.56</i>	<i>-3.03</i>	<i>1.47</i>	<i>9.17</i>
<i>N firm-years</i>	12,700	12,700	12,700	12,700

Notes: This table reports the fraction of imports in expenditure on consumer packaged goods for different education groups using the merged Nielsen-Census sample from Section 4. Importing is proxied by the share of total imports in firm sales. Differential spending on imports is decomposed into “within” and “between” components for 6-digit I-O codes (“industries”) and for Nielsen product modules (“product modules”) according to equation (A27). Firms are weighted by the square-root of Nielsen sales. Standard errors are shown in parentheses.

Table 4: Spending on Imports by Education Group, Motor Vehicle Sample

	By Trading Partner			By Purchase Type		By Vehicle Type	
	All Countries	Outside NAFTA	NAFTA	New	Used	Cars	SUVs
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
All, %	44.40	18.51	25.89	44.93	44.04	49.76	38.59
College, %	47.74	24.67	23.07	47.30	48.13	53.94	39.90
Non-college, %	42.66	15.29	27.37	43.08	42.42	47.32	37.99
College minus non-college, p.p.	+5.08	+9.37	-4.30	+4.22	+5.71	+6.62	+1.92
	(0.21)	(0.24)	(0.18)	(0.30)	(0.29)	(0.27)	(0.30)
<i>as % of avg. import spending</i>	<i>+11.43</i>	<i>+50.64</i>	<i>-16.60</i>	<i>+9.40</i>	<i>+12.96</i>	<i>+13.31</i>	<i>+4.96</i>
<i>N</i> auto purchases	99,278	99,278	99,278	38,164	60,592	51,662	47,616
<i>N</i> brands	45	45	45	44	45	45	41

Notes: This table reports the shares of purchases of imported motor vehicles (cars and SUVs) as a fraction of the total, by education group. The merged dataset measures imports at the level of brands, linking the CEX to Ward’s data, as described in Section 5. Columns (1) to (3) use the full sample of purchases and distinguish between imports from NAFTA and other countries. Columns (4) and (5) decompose the sample into purchases of new and used cars (excluding CEX purchases with missing information on whether the vehicle is new or used), while columns (6) and (7) split purchases into cars and SUVs. Brands are listed in Online Appendix Table A6. Standard errors clustered by CEX household are shown in parentheses.

Table 5: Relationship between Consumer Education and Imports of Assembled Cars and Car Parts across Manufacturers

	Imports as % of Car Sales		Imports as % of Car Sales	
	Assembled Cars Only	Assembled Cars & Car Parts	Assembled Cars Only	Assembled Cars & Car Parts
	(1)	(2)	(3)	(4)
% of New Cars Sold to College Graduates	1.031 (0.326)	0.918 (0.317)		
% of Used Cars Sold to College Graduates			1.565 (0.305)	1.425 (0.290)
<i>N</i> firms	20	20	20	20

Notes: This table shows that imports of car parts do not create large biases for the differential spending of college and non-college consumers on imported cars. The dependent variables in OLS regressions are the shares of imports of assembled cars (“Assembled Cars Only”) or of both assembled cars and car parts (“Assembled Cars & Car Parts”) in the value of car sales. They are computed using the Customs microdata and the Census of Manufacturers at the firm level, as described in Section 5.3. The independent variable is the fraction of sales of each firm to college graduates in the CEX sample of car purchases, 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. The coefficient magnitudes are comparable to the slopes in Figure 6. The sample size is rounded to the nearest 10 to protect confidentiality. Robust standard errors are shown in parentheses.

Table 6: Exposure to Labor Market Effects of Trade by Education Group, Industry Data

	Payroll-weighted Averages							
	Import Penetration		Export Share		Imported Inputs Share		Income Elasticity $\times 100$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
All workers, %	3.97	8.44	4.68	9.39	6.54	12.95	109.92	107.15
College-educated workers, %	3.91	8.05	4.88	9.51	5.84	11.88	115.17	112.70
Non-college educated workers, %	4.03	8.84	4.48	9.27	7.23	14.01	104.73	101.67
College minus non-college, p.p.	-0.13	-0.79	+0.40	+0.23	-1.39	-2.13	+10.44	+11.03
	(0.04)	(0.05)	(0.03)	(0.04)	(0.02)	(0.04)	(0.11)	(0.10)
<i>as % of avg.</i>	<i>-3.21</i>	<i>-9.40</i>	<i>8.61</i>	<i>2.49</i>	<i>-21.25</i>	<i>-16.47</i>	<i>9.50</i>	<i>10.29</i>
→ Between goods and services	-1.56	-1.98	-0.92	-1.16	-0.71	-1.09	+1.05	+0.79
	(0.03)	(0.03)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)
→ Within goods and services	+1.43	+1.19	+1.33	+1.39	-0.68	-1.04	+9.40	+10.24
	(0.02)	(0.04)	(0.02)	(0.03)	(0.01)	(0.03)	(0.11)	(0.10)
→ Between subsectors	+1.11	+1.01	+0.80	+0.99	-0.62	-0.69	+7.40	+8.21
	(0.02)	(0.03)	(0.02)	(0.03)	(0.01)	(0.02)	(0.09)	(0.09)
→ Within subsectors	+0.32	+0.18	+0.53	+0.40	-0.06	-0.35	+1.99	+2.03
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.07)	(0.06)
Adjusted for I-O linkages	No	Yes	No	Yes	No	Yes	No	Yes

Notes: This table reports the payroll-weighted averages of several industry characteristics, overall and for college- and non-college educated workers, using the industry-level data from Section 6, which covers 380 industries. It also decomposes the difference between education groups into the within and between components for sectors (goods and services) and subsectors (listed in Table A2), according to equation (A27). The outcomes are imports as % of absorption, exports as % of industry output, imports of intermediate inputs as % of output, and income elasticities. Even columns account for imports, exports, imported inputs, and income elasticities in downstream industries (see Section 2.3 for details).

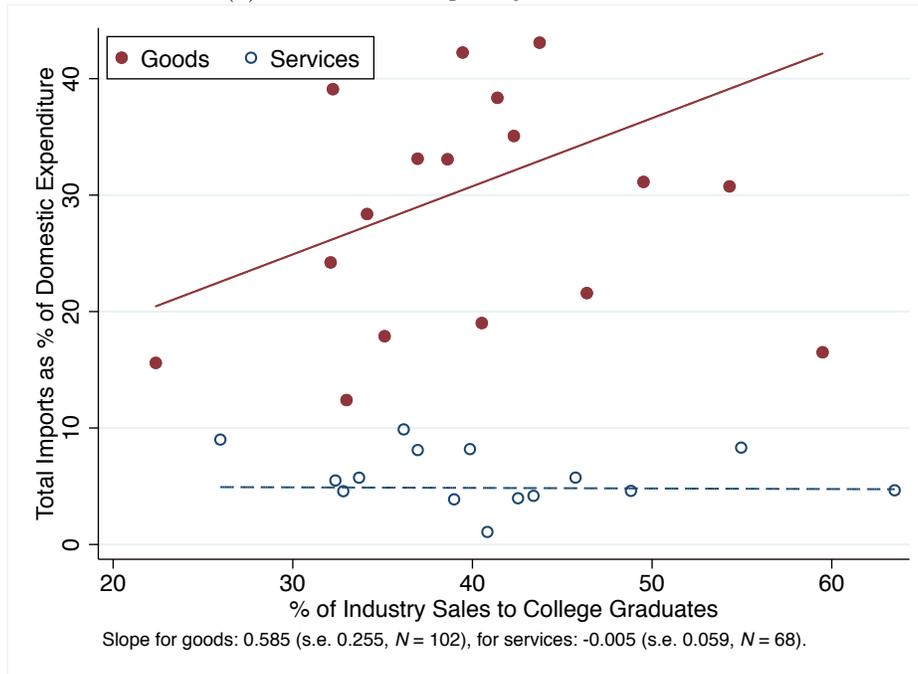
Table 7: Counterfactual Welfare Effects of Trade Liberalizations

(a) Main Results		
	10% Reduction in Trade Barriers	
	All Import and Export Barriers (1)	Import Barriers with China (2)
<i>Average welfare effects, equivalent variation as % of spending</i>		
All	1.705	0.153
College	1.898	0.189
Non-College	1.519	0.119
<i>Distributional effects, college minus non-college, p.p. [as % of avg. welfare effect]</i>		
Overall	+0.379 [22.2%]	+0.070 [45.5%]
→ Expenditure channel, pro-skilled	+0.027 [1.6%]	+0.007 [4.7%]
→ Earnings channel, pro-skilled	+0.352 [20.6%]	+0.063 [40.8%]
(b) Sensitivity of the Earnings Channel to Elasticities		
	10% Reduction in Trade Barriers	
	All Import and Export Barriers (1)	Import Barriers with China (2)
<i>Distributional effects from the earnings channel, college minus non-college, % of avg. welfare effect</i>		
Baseline: $\xi = 3.5, \varepsilon = 1, \rho = 0.2, \sigma_{\text{macro}} = 1.41$	+20.6	+40.8
→ Varying ξ from 1.9 to 5.1	+17.7 to +23.6	+26.1 to +55.7
→ Varying ε from 0.8 to 3.5	+20.9 to +17.5	+41.2 to +36.2
→ Varying ρ from 0 to 1	+22.6 to +12.8	+43.6 to +29.3
→ Varying σ_{macro} from 1.41 to 1.8	+20.6 to +16.2	+40.8 to +31.9
→ Using Broda-Weinstein ξ_j	+19.6	+38.2

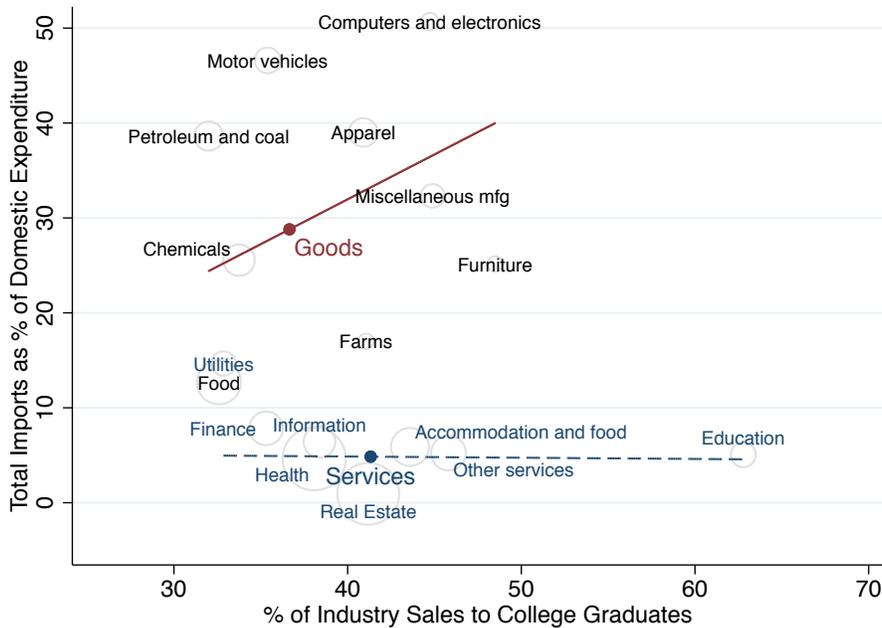
Notes: This table calibrates the welfare effects of trade liberalizations across education groups using the model from Section 2.3 and the reduced-form patterns from Sections 3–6. Panel (a) reports the welfare effects in terms of equivalent variation, expressed as a percentage of initial consumption spending for each education group. The distributional effects are decomposed into the expenditure channel and the earnings channel according to equation (3). Panel (b) shows the sensitivity of the distributional effects from the earnings channel to the choice of structural elasticities. Using the notation from the model in Section 2, ξ denotes the trade elasticity, ε the elasticity of substitution between industries (6-digit I-O codes), ρ the elasticity of substitution between sectors (goods and services), and σ_{macro} the elasticity of substitution between skilled and unskilled labor (workers with and without a college degree). For each of these elasticities, we consider a plausible range of values in light of the literature (see the main text for a complete discussion).

Figure 1: Industry Import Shares and Consumer Base

(a) Industries Grouped by Consumer Base

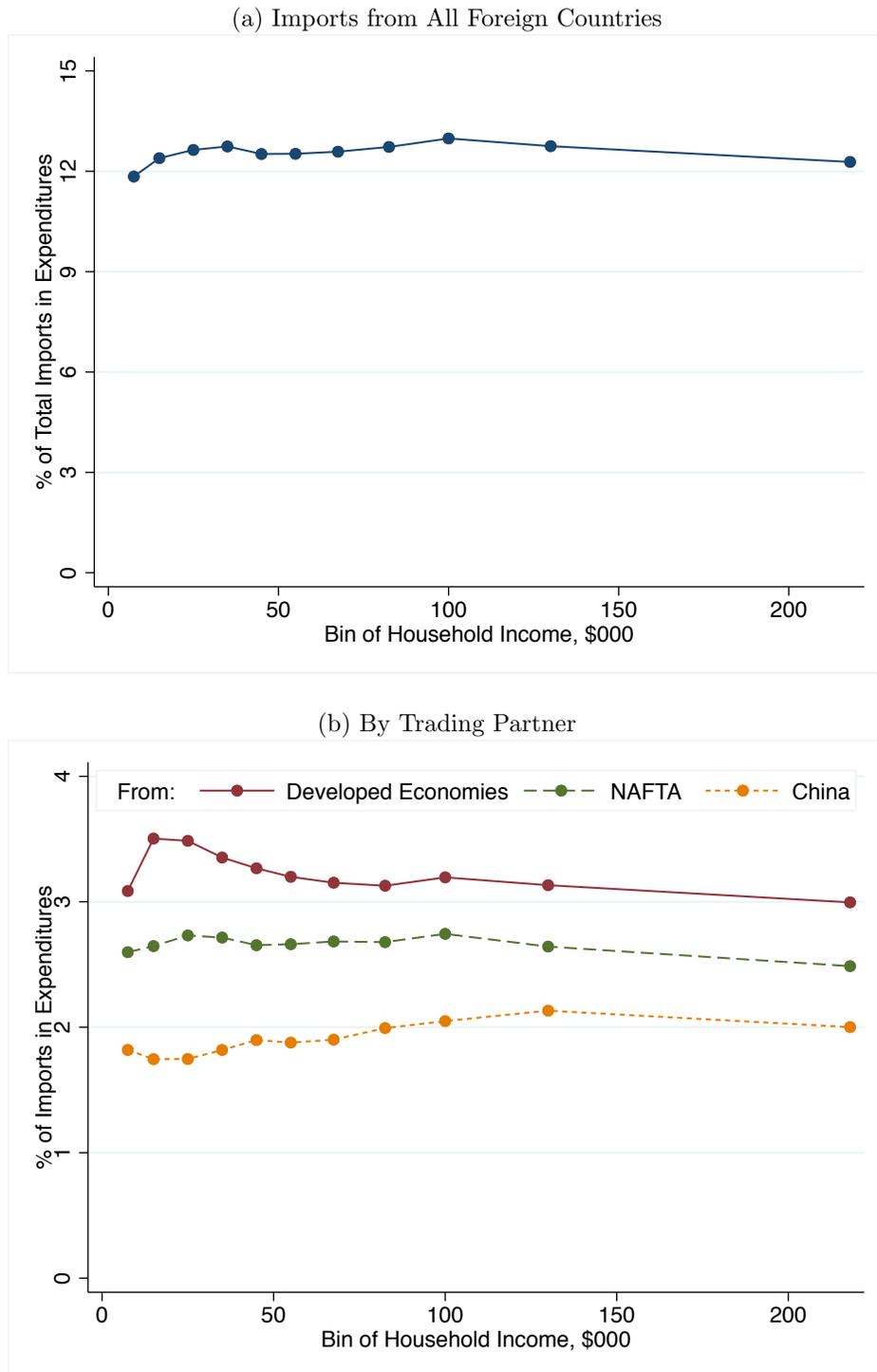


(b) Industries Grouped by Subsector



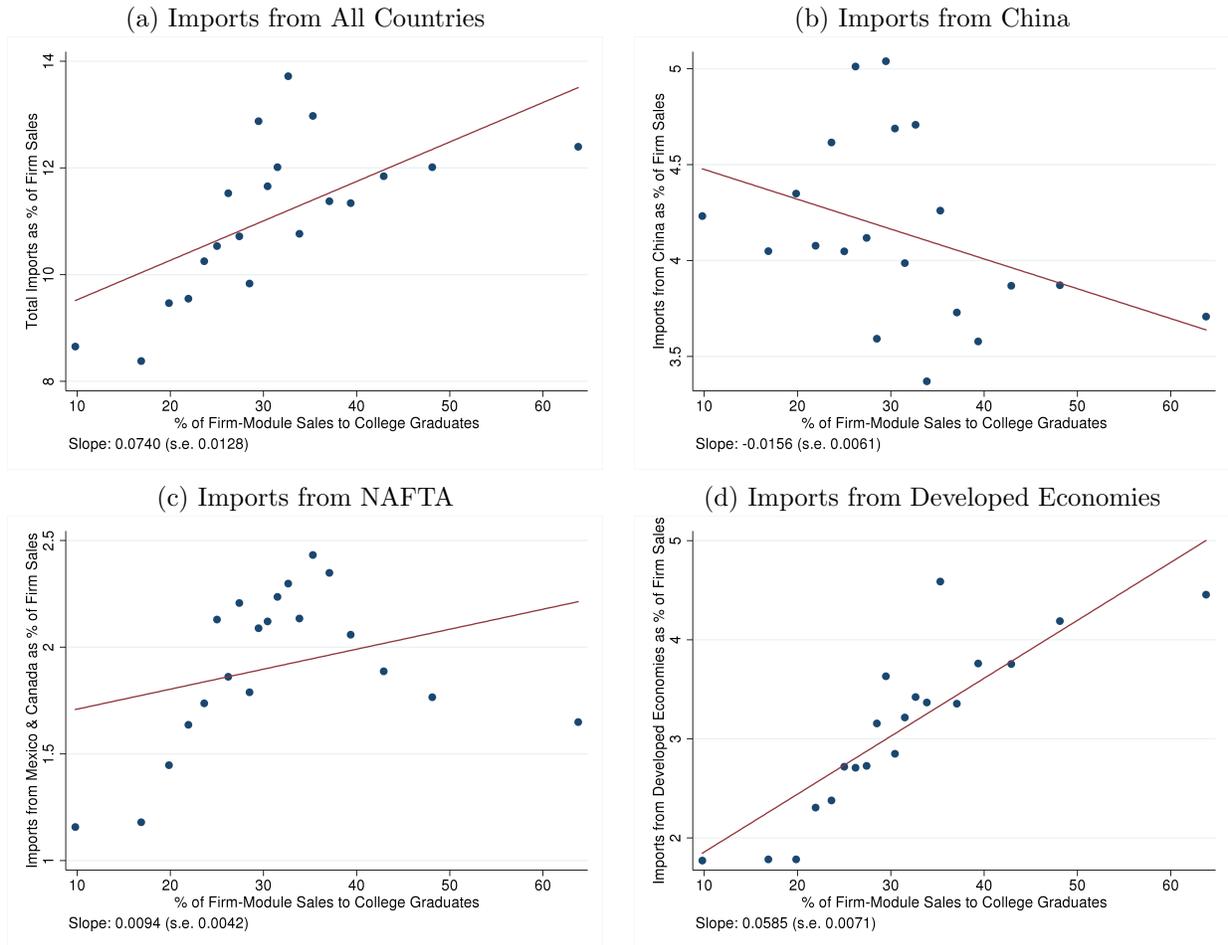
Notes: The binned scatterplot in Panel (a) groups six-digit I-O industries within each sector into bins by consumer base (% of industry sales to college graduates) and reports total import content (the share of direct and indirect imports from all countries in final expenditures) in these industries. In Panel (b), each circle corresponds to a subsector from Table A2, and the circle size indicates final spending. Subsectors that account for less than 3% of the sectoral expenditure are not shown. Industry-level data from Section 3 are employed in both panels. The weighted mean of consumer base captures the share of total expenditures by college graduates in the economy (40.2%, compared to their population share of 30.1%).

Figure 2: Import Spending by Consumer Income Bin, Industry-Level Data



Notes: These binned scatterplots group CEX panelists into 11 bins by household income before tax. They report the average share of total (direct and indirect) imports in the spending of each bin, computed using the industry-level data from Section 3. Panel (a) accounts for all imports (including services), whereas Panel (b) measures only imports of goods from 34 developed economies, NAFTA countries, and China.

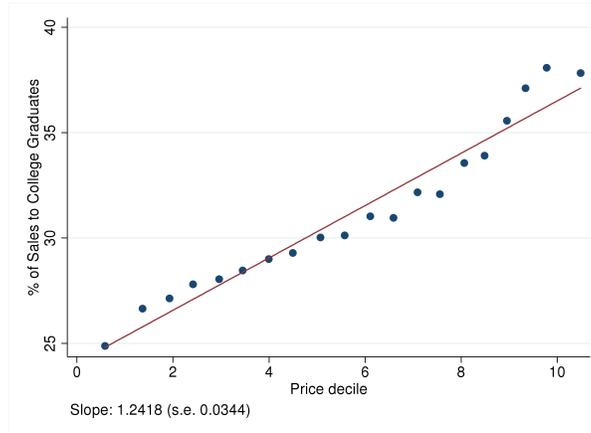
Figure 3: Import Shares and Consumer Base, Merged Nielsen-Census Sample



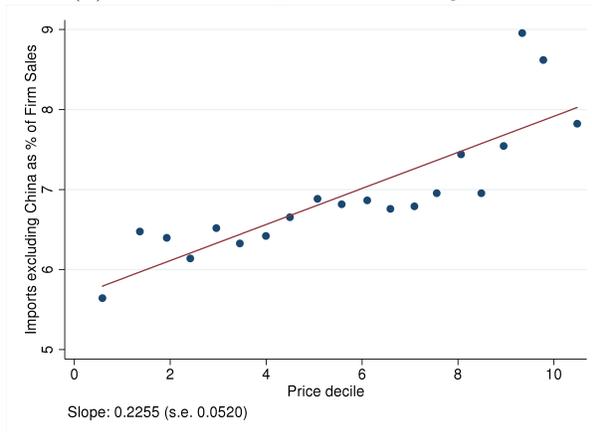
Notes: These binned scatterplots group firm-module-year cells into 20 bins by consumer base (the fraction of Nielsen sales to college graduates). The vertical axis shows the average share of imports in sales measured at the firm level in the Census, for all imports in Panel (a) and from specific groups of origin countries in the other panels. Firms are weighted by the square-root of their Nielsen sales (weights are split across barcodes of the same firm proportionally to sales). Fixed effects of I-O industries by year are absorbed.

Figure 4: The Role of Product Quality

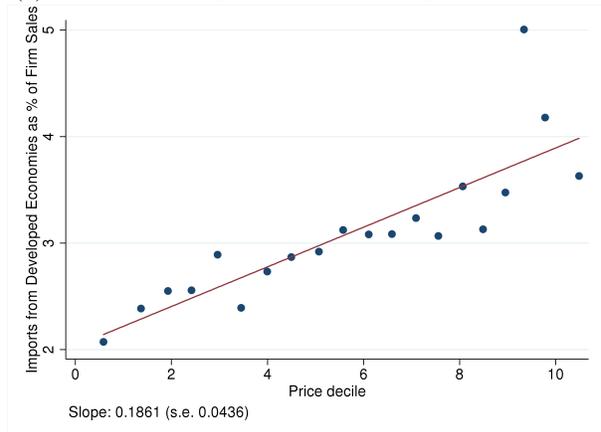
(a) Prices and Consumer Base



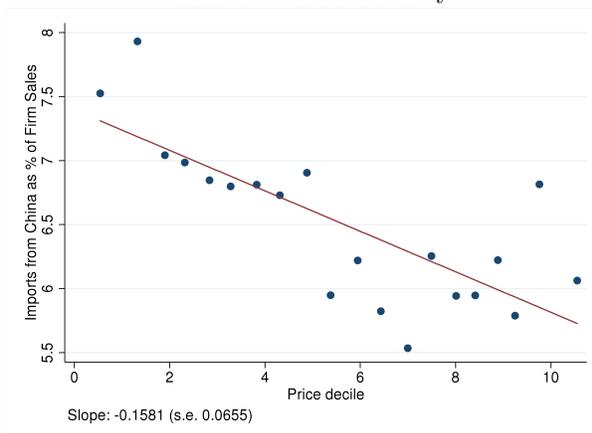
(b) Prices and Imports Excluding China



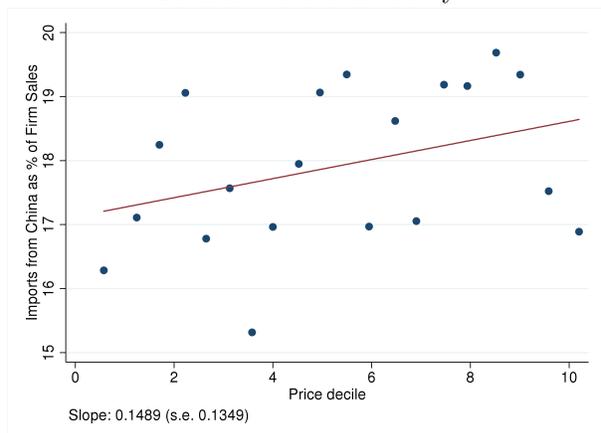
(c) Prices and Imports from Developed Economies



(d) Prices and Imports from China, Health & Household only

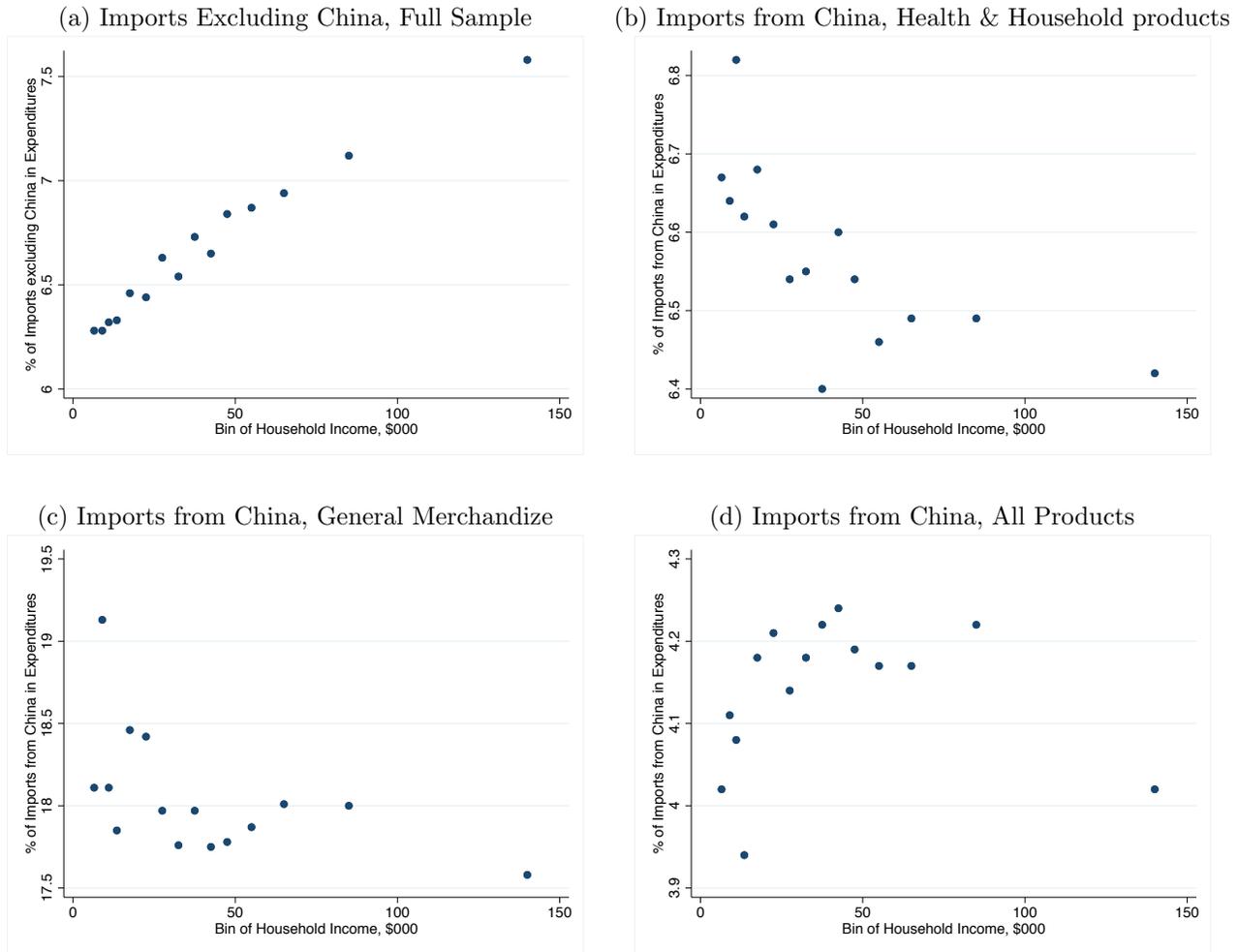


(e) Prices and Imports from China, General Merchandise only



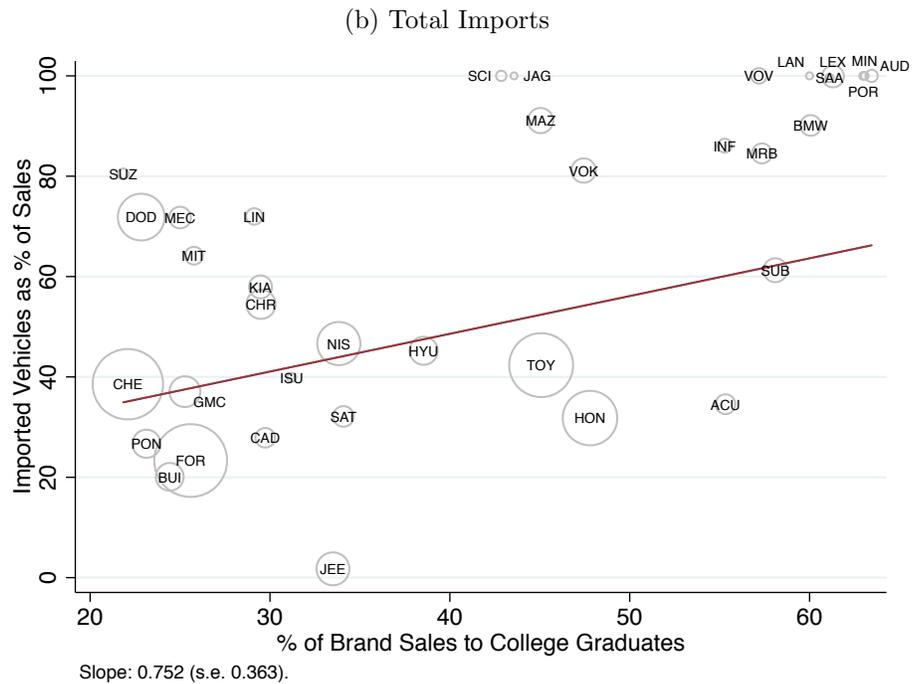
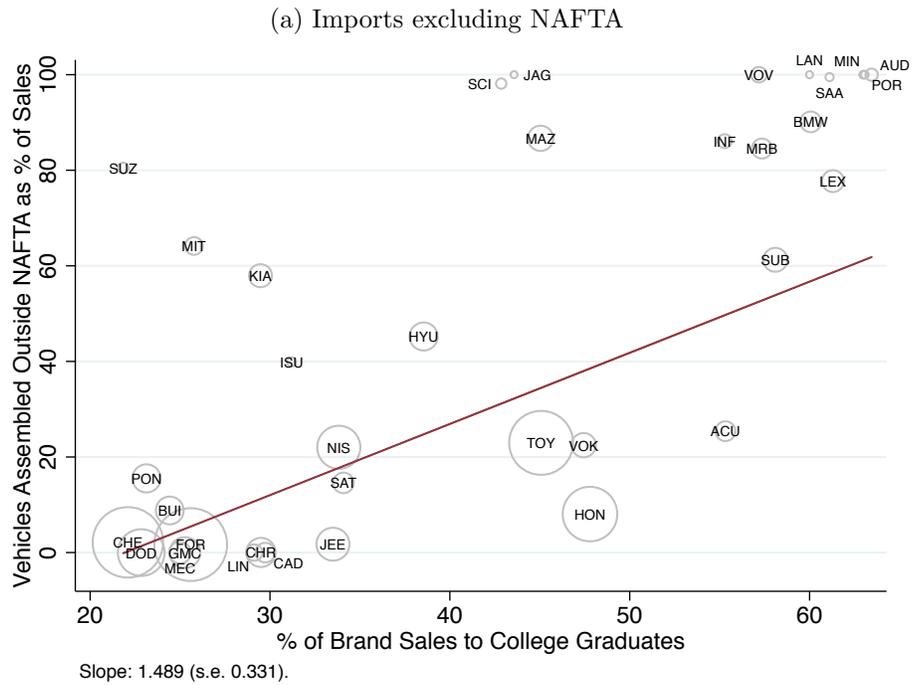
Notes: These binned scatterplots show average % of sales to college graduates and import shares by decile of barcode prices within their respective product modules. Import shares are computed at the firm-level. The analysis is performed on the sample of firm-year-module-decile cells. Product modules which include barcodes with quantity measured in different units (e.g. ounces vs. counts) are decomposed by measurement unit. Firms are weighted by the square-root of their Nielsen sales, and weights are decomposed across barcodes of the same firm proportionally to sales. Fixed effects of modules by year are absorbed.

Figure 5: Import Spending by Consumer Income Bin, Merged Nielsen-Census Sample



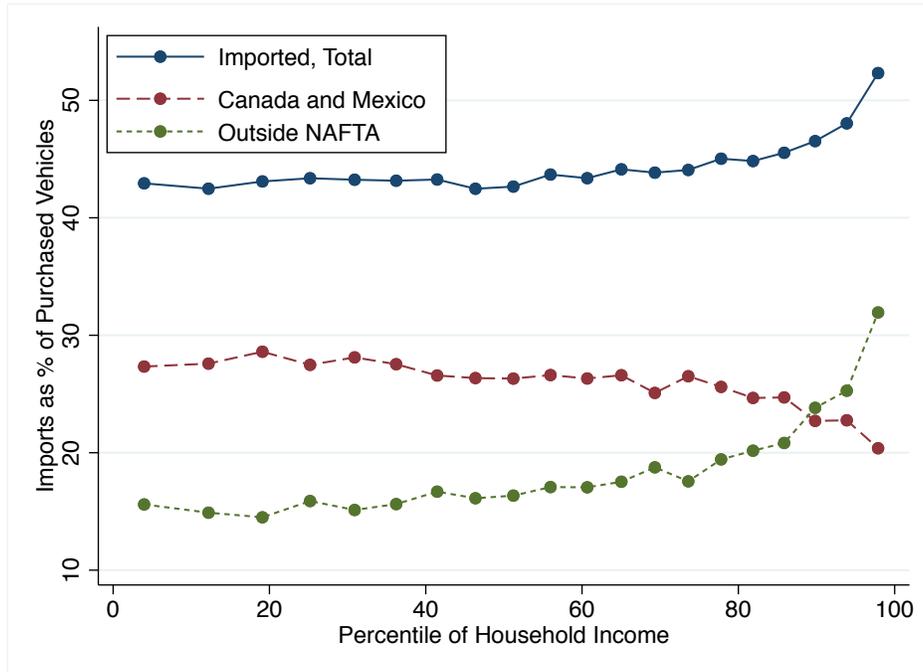
Notes: These binned scatterplots group Nielsen panelists into 15 bins by household income. They report the average share of imports in the spending of each bin, computed using the merged Nielsen-Census sample from Section 4. Panel (a) accounts for imports from countries other than China. The other panels measure imports from China: for Health and Household products (Panel (b)), General Merchandize (Panel (c)), and overall (Panel (d)). The upward slope in Panel (d) is a consequence of compositional differences only: rich people spend more on general merchandize and less on food (see online Appendix Table A5).

Figure 6: Imports Shares and Consumer Base across Auto Brands



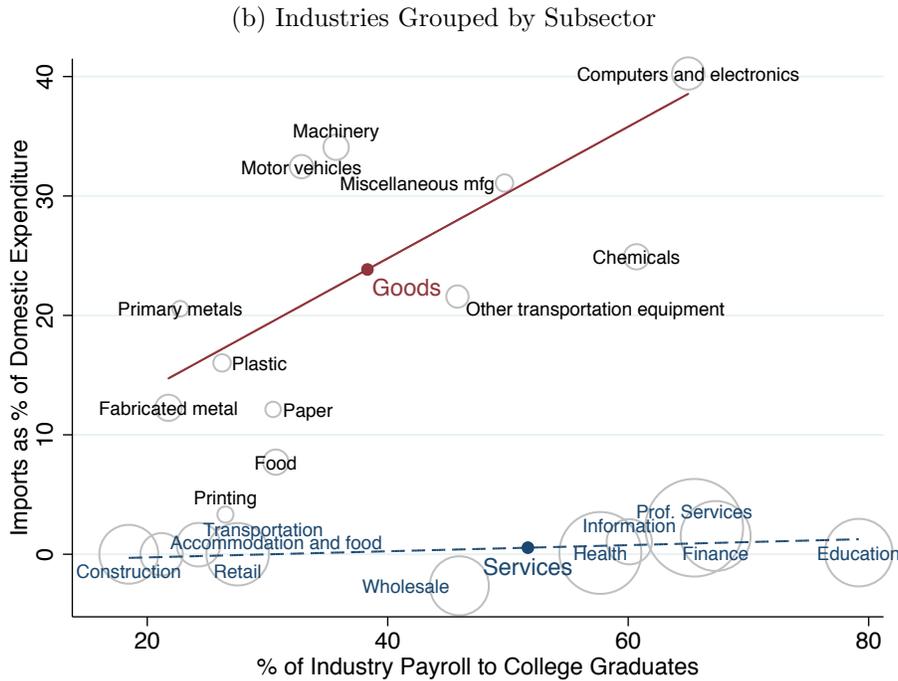
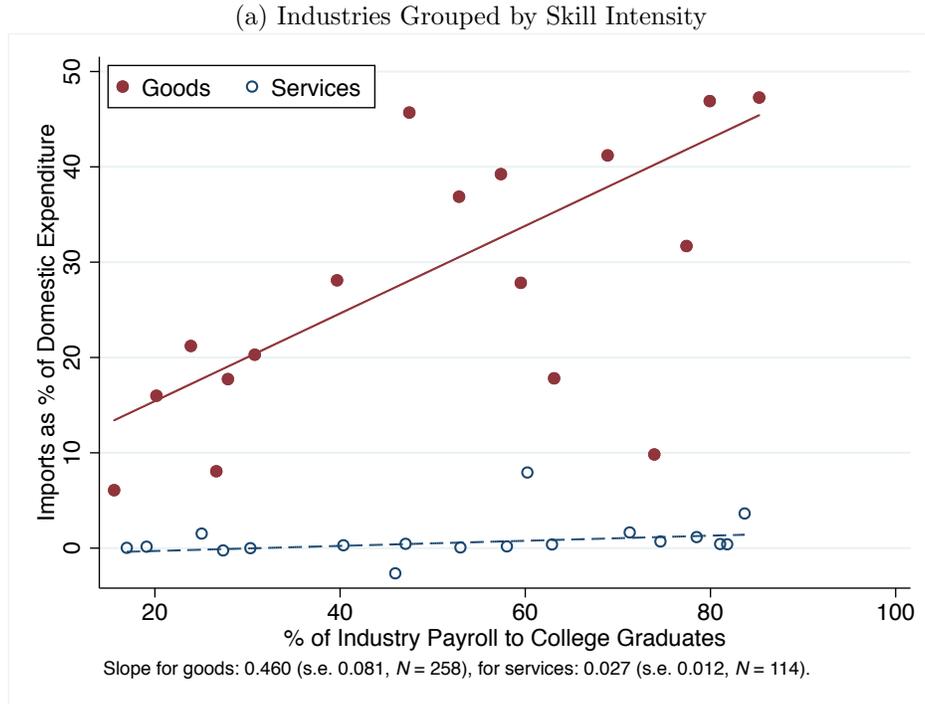
Notes: Each circle corresponds to a brand of motor vehicles (cars or SUVs). The import shares on the vertical axis are based on the Ward's data, aggregated from models into brands; imports from NAFTA are excluded in Panel (a), while imports from trading partners are accounted for in Panel (b). The shares of vehicles of each brand sold to college graduates on the horizontal axis is from CEX. 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. Brands are listed in online Appendix Table A6.

Figure 7: Fraction of Imported Cars by Household Income Bins



Notes: These binned scatterplots split motor vehicle purchases in the CEX into equally-sized bins by the percentile of the owner’s household income (among all surveyed households) in the year of the survey. Each car in the data is assigned a probability of being imported (overall or from NAFTA countries specifically) based on the average import share of the car brand in the Ward’s data.

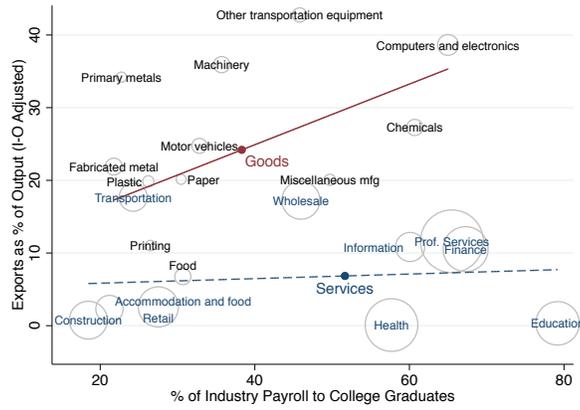
Figure 8: Import Penetration and Skill Intensity across Industries



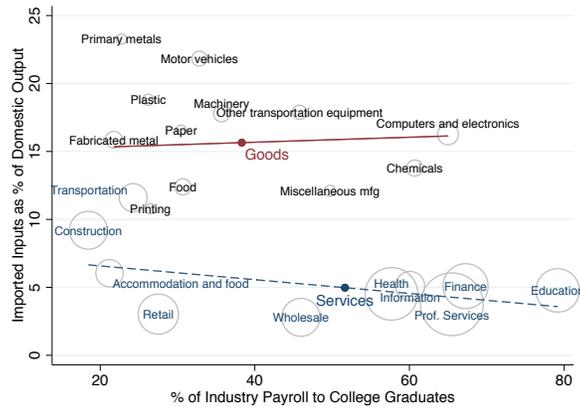
Notes: The binned scatterplot in Panel (a) groups six-digit I-O industries within each sector into bins by skill intensity (payroll share of college graduates) and reports the import penetration (the share of direct imports from all countries in absorption) in these industries. In Panel (b), each circle corresponds to a subsector from Table A2, and the circle size indicates payroll (subsectors that account for less than 3% of the sectoral payroll are not shown). Industry-level data from Section 6 are used in both panels.

Figure 9: Additional Industry-Level Outcomes and Skill Intensity

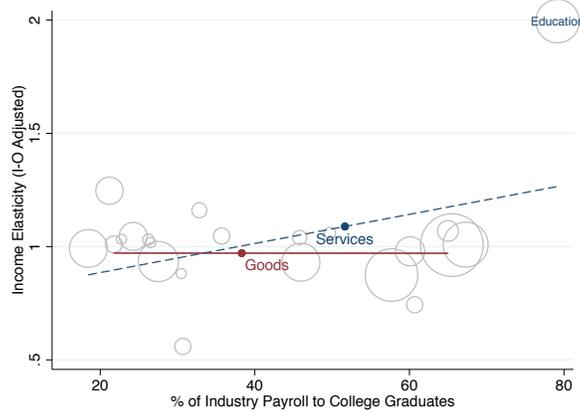
(a) Export Share as % of Output, I-O Adjusted



(b) Imported Intermediate Inputs as % of Output

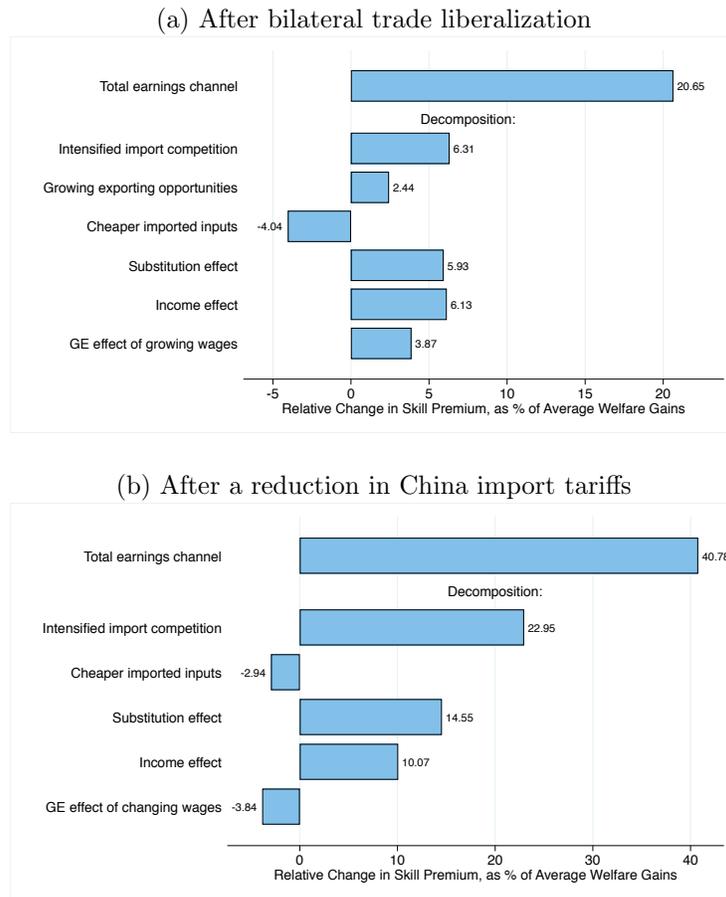


(c) Income Elasticity, I-O Adjusted



Notes: This figure uses industry-level data from Section 6 to show the relationship between skill intensity (payroll share of college graduates) and three outcomes: the share of exports (including exports that happen through domestic customers) in industry output in Panel (a), the share of imported intermediate inputs in industry output in Panel (b), and the weighted average income elasticity corresponding to the final demand in the industry and its domestic customers in Panel (c). The outcomes are measured according to the model in Theory Appendix A.2. Each circle corresponds to a subsector and the circle size indicates total payroll. Subsectors that account for less than 3% of the sectoral payroll are not shown. For clarity, Panel (c) only labels the Education subsector that is most important to understand the patterns.

Figure 10: Decomposition of the Earnings Channel



Notes: This figure decomposes the distributional effects via the earnings channel corresponding to a bilateral trade liberalization between the U.S. and all trading partners (Panel (a)) or a reduction in tariffs on Chinese imports (Panel (b)). This decomposition is based on the model from Section 2 and uses the industry-level data from Sections 3 and 6 and the structural parameters from Section 7.

For Online Publication

**Appendix to “The Distributional Effects of Trade:
Theory and Evidence from the United States”**

Kirill Borusyak, Princeton University
Xavier Jaravel, London School of Economics
October 2018

Contents

A Theory Appendix	A1
A.1 Model without Input-Output Linkages	A1
A.2 General Model	A7
A.3 Skill-Biased Import Competition	A11
A.4 Roy Model	A13
A.5 Two Decompositions	A15
B Data Replication Appendix	A18
B.1 Consumer Expenditure Survey	A18
B.2 BEA Input-Output Table	A19
B.3 Linked Nielsen-Census Dataset	A20
B.4 Datasets on Motor Vehicles	A25
B.5 Combining Estimates on Differential Spending on Imports	A27
B.6 Using QCEW to Impute Skill Intensity	A28
B.7 Census Data for Skill Intensity and Exports	A29
C Econometric Appendix	A30
C.1 Inference for the Expenditure Channel Decomposition	A30
C.2 Estimation of Income Elasticities	A32
C.3 Bias-Corrected Estimation of Consumption Segmentation	A33
D Additional Results and Robustness	A35
D.1 The Segregation Channel	A35
D.2 Differences in Spending on Imports of Consumer Packaged Goods	A36
D.3 Differences in Labor Market Exposure to Trade	A39
D.4 The Earnings Channel for Capital Owners vs. Workers	A40
D.5 Calibrations for Observed Changes in Trade Costs	A41
Additional Tables and Figures	A46

A Theory Appendix

A.1 Model without Input-Output Linkages

Equilibrium Conditions. The equilibrium is defined by a set of quantities and prices that satisfy five standard conditions:

1. Profit maximization by domestic and foreign producers;
2. Utility maximization for each type of domestic agents: $\max_{\{Q_{jc}^i\}} \mathcal{U}$ s.t. $\sum_{j,c} p_{jc} Q_{jc}^i = \zeta_i w_i$;
3. Export demand: $Q_{jH}^{\text{Export}} = a_j^{\text{Export}} \left(p_{jH} \tau_j^* \right)^{-\xi_j}$ for each j ;
4. Product market clearing for domestic varieties: $Q_{jH} = L_S Q_{jH}^S + L_U Q_{jH}^U + Q_{jH}^{\text{Export}} = F_j \left(L_S^j, L_U^j \right)$ for each j ;
5. Labor market clearing for each type of agents: $\sum_j L_i^j = L_i$ for $i = S, U$.

Proof of (10). We start from the labor market clearing condition, expressed in value terms. For the skilled workers, $w_S L_S = \sum_j w_S L_S^j = \sum_j V A_j \cdot v_j$, which in log-changes becomes

$$\hat{w}_S = \sum_j e_S^j \cdot \left(\widehat{V A}_j + \hat{v}_j \right). \quad (\text{A1a})$$

Similarly for the unskilled, $w_U L_U = \sum_j w_U L_U^j = \sum_j V A_j \cdot (1 - v_j)$, thus

$$\hat{w}_U = \sum_j e_U^j \cdot \left(\widehat{V A}_j + \widehat{1 - v}_j \right). \quad (\text{A1b})$$

To solve for the change in the payroll shares of the skilled and unskilled groups (\hat{v}_j and $\widehat{1 - v}_j$, respectively), we note that $v_j / (1 - v_j) = w_S L_S^j / w_U L_U^j$. By definition of the local elasticity of substitution σ_j , this implies:

$$\left(\widehat{\frac{v_j}{1 - v_j}} \right) = (1 - \sigma_j) (\hat{w}_S - \hat{w}_U).$$

Expanding the left-hand side using the standard log-differentiation rules, we obtain:⁴⁰

$$\begin{aligned} \hat{v}_j &= (1 - \sigma_j) (1 - v_j) (\hat{w}_S - \hat{w}_U), \\ \widehat{1 - v}_j &= -(1 - \sigma_j) v_j (\hat{w}_S - \hat{w}_U). \end{aligned}$$

Plugging these into (A1a) and (A1b) and taking the difference between skilled and unskilled groups yields

$$\hat{w}_S - \hat{w}_U = \sum_j \left(e_S^j - e_U^j \right) \widehat{V A}_j + \sum_j (1 - \sigma_j) \left(e_S^j (1 - v_j) + e_U^j v_j \right) \cdot (\hat{w}_S - \hat{w}_U). \quad (\text{A2})$$

⁴⁰We use $\partial \log(z/(1-z)) / \partial \log z = 1/(1-z)$ and $\partial \log(1/(1-z)) / \partial \log z = -z/(1-z)$.

Denoting the value added share of industry j by $e_j = VA_j/GDP$ (where $GDP = \sum_j VA_j$), we can represent e_j^S as

$$e_j^S = \frac{w_S L_S^j}{w_S L_S} = \frac{VA_j}{GDP} \cdot \frac{w_S L_S^j / VA_j}{w_S L_S / GDP} = e_j \cdot \frac{v_j}{\bar{v}},$$

and similarly $e_j^U = e_j (1 - v_j) / (1 - \bar{v})$. This implies

$$e_j^S (1 - v_j) + e_j^U v_j = e_j \left(\frac{v_j (1 - v_j)}{\bar{v}} + \frac{v_j (1 - v_j)}{1 - \bar{v}} \right) = e_j \frac{v_j (1 - v_j)}{\bar{v} (1 - \bar{v})}.$$

Plugging this into (A2), we finally obtain (10):

$$\begin{aligned} \hat{w}_S - \hat{w}_U &= \Delta_{VA} [\widehat{VA}_j] - \mathbb{E}_{VA} \left[\frac{v_j (1 - v_j)}{\bar{v} (1 - \bar{v})} (\sigma_j - 1) \right] \cdot (\hat{w}_S - \hat{w}_U) \\ &= \frac{\Delta_{VA} [\widehat{VA}_j]}{1 + \mathbb{E}_{VA} \left[\frac{v_j (1 - v_j)}{\bar{v} (1 - \bar{v})} \cdot (\sigma_j - 1) \right]} \equiv \frac{\Delta_{VA} [\widehat{VA}_j]}{\sigma_{\text{within}}}. \end{aligned}$$

We note that σ_{within} is higher when skills are more substitutable within each industry (higher σ_j) and also when skill intensity is more homogenous across industries. Indeed, when technologies in each industry are such that one type of labor (sometimes skilled and sometimes unskilled) is much more productive, there is little room for adjusting industry labor mixes in response to wage shocks, and $\sigma_{\text{within}} \approx 1$. If instead all industries employ skilled and unskilled labor in the same proportions, σ_{within} is just the size-weighted average of σ_j , which is above one as long as skills are substitutes. To see this, observe that the weights applied to $\sigma_j - 1$ aggregate to

$$\mathbb{E}_{VA} \left[\frac{v_j (1 - v_j)}{\bar{v} (1 - \bar{v})} \right] = \frac{\bar{v} - \bar{v}^2 - \text{Var}[v_j]}{\bar{v} (1 - \bar{v})} = 1 - \text{Segm}_{\text{prod}},$$

where $\text{Segm}_{\text{prod}} = \text{Var}[v_j] / \bar{v} (1 - \bar{v})$ is the production segmentation index, which measures the heterogeneity of industries by skill intensity.

Log-Linearization of Non-Homothetic Nested CES Demand. Here we show that non-homothetic nested CES preferences defined implicitly by (1) yield a very intuitive log-linear approximation for the *change* in demand after a set of wage and price shocks, even though demand functions do not have a closed-form solution. It combines both nested CES as non-homothetic CES as special cases.

We will fix one type of agents and therefore suppress the i index, and to understand the demand behavior in the general case, we treat the set of shocks to consumer's expenditure and prices, \hat{X} and \hat{p}_j , as exogenous. We also assume the parameter restrictions which guarantee that preferences are well-defined. In particular this requires $\varepsilon_r \neq 1$, since non-homothetic Cobb-Douglas preferences cannot be

globally defined (Hanoch 1975; Comin et al. 2016).⁴¹

Conditional on the utility level \mathcal{U} at the optimal bundle of goods, preferences reduce to nested CES, which has a well-known demand structure. Define the sectoral and overall price indices as

$$\begin{aligned} p_r^* &= \left(\sum_{j \in r} a_j \mathcal{U}^{\varphi_j - 1} p_j^{1 - \varepsilon_r} \right)^{1/(1 - \varepsilon_r)}, \\ \pi^* &= \left(\sum_r p_r^{*1 - \rho} \right)^{1/(1 - \rho)}. \end{aligned} \quad (\text{A3})$$

Then

$$\mathcal{U} = X/\pi^*, \quad (\text{A4})$$

and spending on good j satisfies

$$X_j = X \cdot s_j \equiv X \cdot \underbrace{\frac{a_j \mathcal{U}^{\varphi_j - 1} p_j^{1 - \varepsilon_r}}{p_r^{*1 - \varepsilon_r}}}_{s_{j|r}} \cdot \underbrace{\frac{p_r^{*1 - \rho}}{\pi^{*1 - \rho}}}_{s_r}. \quad (\text{A5})$$

Define $\lambda_j = \frac{\varphi_j - 1}{1 - \varepsilon_r}$, $\lambda_r = \sum_{j \in r} s_{j|r} \lambda_j$, and $\lambda = \sum_r s_r \lambda_r$, which are observable at the original equilibrium, given preference parameters. Then log-differentiating (A3) yields:

$$\hat{p}_r^* = \sum_j s_{j|r} \left(\hat{p}_j + \lambda_j \hat{\mathcal{U}}^* \right) = \hat{p}_r + \lambda_r \hat{\mathcal{U}}^* \quad \text{and} \quad (\text{A6a})$$

$$\hat{\pi}^* = \sum_r s_r \hat{p}_r^* = \hat{\pi} + \lambda \hat{\mathcal{U}}^*, \quad (\text{A6b})$$

where $\hat{\mathcal{U}}^* = d \log \mathcal{U}$ is the relative change in the *cardinal utility*. Together with (A4), (A6b) implies

$$\hat{\mathcal{U}}^* = \hat{X} - \hat{\pi}^* = \frac{\hat{X} - \hat{\pi}}{1 + \lambda}. \quad (\text{A7})$$

This equation relates changes in the cardinal utility to observable objects only: the money metric (change in the total expenditure minus the Laspeyres price index) and the spending shares at the original equilibrium (which enter λ). We can now express the changes in demand also in terms of observables: log-differentiating (A5) and plugging in (A6) and (A7),

$$\begin{aligned} \hat{X}_j &= \hat{X} + (\varphi_j - 1) \hat{\mathcal{U}}^* + (1 - \varepsilon_r) (\hat{p}_j - \hat{p}_r^*) + (1 - \rho) (\hat{p}_r^* - \hat{\pi}^*) \\ &= \hat{X} + (1 - \varepsilon_r) (\hat{p}_j - \hat{p}_r) + (1 - \rho) (\hat{p}_r - \hat{\pi}) + (\psi_j - 1) (\hat{X} - \hat{\pi}), \end{aligned} \quad (\text{A8})$$

⁴¹In the application we will allow for $\varepsilon_r = 1$, interpreted as $\varepsilon_r \rightarrow 1$, which is sufficient for us since we are only interested in the local behavior of demand.

where

$$\psi_j = 1 + \frac{(1 - \varepsilon_r)(\lambda_j - \lambda_r) + (1 - \rho)(\lambda_r - \lambda)}{1 + \lambda}. \quad (\text{A9})$$

According to (A8), the change in spending on industry j has four components. The first three are identical to conventional nested CES, capturing the change in total expenditure (i.e., in income), reallocation of demand within the sector and across sectors. The fourth is the income effect, shaped by the income elasticity ψ_j . When the money metric of utility, which is an observable measure of real income, goes up, spending on income-elastic products with $\psi_j > 1$ increases. Within each sector, income elasticities are higher in industries with higher φ_j , but the comparison across sectors is less straightforward. Theoretically, income elasticities differ by income (via λ_r and λ) but we ignore these differences across consumer groups and across equilibria, viewing the ψ_j as fixed industry characteristics, as in Aguiar and Bils (2015).

Proof of (11)–(12). From the market clearing condition for domestic products, the value of domestic output (or equivalently value added) combines domestic and export sales: $VA_j = X_{jH}^{\text{Final}} + X_j^{\text{Export}}$, where $X_{jH}^{\text{Final}} = X_{jH}^S + X_{jH}^U$. In log-differences,

$$\begin{aligned} \widehat{VA}_j &= \text{Dom share}_j \cdot \hat{X}_j^{\text{Final}} + \text{Export share}_j \cdot \hat{X}_j^{\text{Export}} \quad \text{and} \quad (\text{A10}) \\ \hat{X}_j^{\text{Final}} &= \mu_j \hat{X}_{jH}^S + (1 - \mu_j) \hat{X}_{jH}^U, \end{aligned}$$

where μ_j is the fraction of industry final sales to the skilled group, which we refer to as consumer base.

We combine the trade-induced price changes from Step 1 with the demand system to solve for the domestic and foreign consumers' demand changes. First, using the simple structure of foreign demand and the equation for domestic price changes (5),

$$\begin{aligned} \hat{X}_j^{\text{Export}} &= (1 - \xi_j)(\hat{p}_{jH} + \hat{\tau}^*) \\ &= (1 - \xi_j)(\hat{w} + \hat{\tau}^* + (v_j - \bar{v})(\hat{w}_S - \hat{w}_U)). \end{aligned} \quad (\text{A11})$$

Second, equation (A8) characterized the change in the spending of a group- i consumer, who has non-homothetic nested CES preferences, on the industry j 's composite good. Combining it with CES preferences over varieties from different countries and using $\hat{X}_i = \hat{w}_i$, we obtain

$$\hat{X}_{jH}^i = \hat{w}_i + (1 - \xi_j)(\hat{p}_{jH} - \hat{p}_j) + (1 - \varepsilon_r)(\hat{p}_j - \hat{p}_{ir}) + (1 - \rho)(\hat{p}_{ir} - \hat{\pi}_i) + (\psi_j - 1)(\hat{w}_i - \hat{\pi}_i) \quad (\text{A12})$$

where $\hat{p}_{ir} = \sum_{j \in r} s_{j|r}^i \hat{p}_j$ is the group-specific sectoral price index and $s_{j|r}^i = s_j^i / s_r^i$ is the spending share within the sector. (A12) represents the change in domestic spending on domestic varieties as a sum of five terms, representing growth of domestic income, reduction of domestic prices relative to the industry composite, cross-price effects across industries and sectors, and income effects. Averaging \hat{X}_{jH}^i between

the two consumer groups and expressing everything in terms of averages and differences between the groups, we obtain:

$$\begin{aligned}
\hat{X}_{jH}^{\text{Final}} &= \hat{w} + (\mu_j - \bar{\mu}) (\hat{w}_S - \hat{w}_U) \\
&\quad + (1 - \xi_j) (\hat{p}_{jH} - \hat{p}_j) \\
&\quad + (1 - \varepsilon_r) (\hat{p}_j - \hat{p}_r - (\mu_j - \mu_r) (\hat{p}_{Sr} - \hat{p}_{Ur})) \\
&\quad + (1 - \rho) (\hat{p}_r + (\mu_j - \mu_r) (\hat{p}_{Sr} - \hat{p}_{Ur}) - \hat{\pi} - (\mu_j - \bar{\mu}) (\hat{\pi}_S - \hat{\pi}_U)) \\
&\quad + (\psi_j - 1) (\hat{w} - \hat{\pi} + (\mu_j - \bar{\mu}) (\hat{w}_S - \hat{w}_U) - (\mu_j - \bar{\mu}) (\hat{\pi}_S - \hat{\pi}_U)), \tag{A13}
\end{aligned}$$

where $\hat{p}_r \equiv \mu_r \hat{p}_{Sr} + (1 - \mu_r) \hat{p}_{Ur} = \mathbb{E}_{\text{Final}} [\hat{p}_j | r]$ is the sectoral price index for all final consumption.

It remains to characterize various price indices. Equations (5) and (6) characterize producer and consumer price changes by industry, \hat{p}_{jH} and \hat{p}_j , respectively, together implying:

$$\hat{p}_{jH} - \hat{p}_j = -IP_{jc} \hat{\tau} + IP_j \hat{w} + IP_j (v_j - \bar{v}) (\hat{w}_S - \hat{w}_U).$$

Similarly,

$$\begin{aligned}
\hat{p}_j - \hat{p}_r &= (IP_{jc} - \mathbb{E}_{\text{Final}} [IP_{jc} | r]) \hat{\tau} - (IP_j - \mathbb{E}_{\text{Final}} [IP_j | r]) \hat{w} \\
&\quad + ((v_j - \bar{v}) (1 - IP_j) - \mathbb{E}_{\text{Final}} [(v_j - \bar{v}) (1 - IP_j) | r]) (\hat{w}_S - \hat{w}_U), \\
\hat{p}_r - \hat{\pi} &= \mathbb{E}_{\text{Final}} [\hat{p}_j | r] - \mathbb{E}_{\text{Final}} [\hat{p}_j], \\
\hat{p}_{Sr} - \hat{p}_{Ur} &= \Delta_{\text{Final}} [\hat{p}_j | r] \equiv \sum_{j \in r} (s_{j|r}^S - s_{j|r}^U) \hat{p}_j, \quad \text{and} \\
\hat{\pi}_S - \hat{\pi}_U &= \Delta_{\text{Final}} [\hat{p}_j],
\end{aligned}$$

where in the last three lines industry price indices can again be plugged in from (6). We substitute these expressions in (A13) and then to (A10), and rearrange terms, isolating those with $\hat{\tau}$, $\hat{\tau}^*$, \hat{w} , and $\hat{w}_S - \hat{w}_U$. The coefficients at these terms define η_j^{import} , $-\eta_j^{\text{export}}$, $\eta_j^{\text{avg wage}}$, and $-\eta_j^{\text{skill prem}}$, respectively. With some algebra, we arrive at (12b), (12c), and

$$\begin{aligned}
\eta_j^{\text{import}} &= \text{Dom share}_j \cdot \{(\xi_j - 1) \cdot IP_{jc} + (\varepsilon_r - 1) \cdot (\mathbb{E}_{\text{Final}} [IP_{jc} | r] - IP_{jc}) \\
&\quad + (\rho - 1) \cdot (\mathbb{E}_{\text{Final}} [IP_{jc}] - \mathbb{E}_{\text{Final}} [IP_{jc} | r]) - (\psi_j - 1) \cdot \mathbb{E}_{\text{Final}} [IP_{jc}] \\
&\quad + (\varepsilon_r - \rho) (\mu_j - \mu_r) \Delta_{\text{Final}} [IP_{jc}] - (\psi_j - \rho) (\mu_j - \bar{\mu}) \Delta_{\text{Final}} [IP_{jc}]\}. \tag{A14}
\end{aligned}$$

The two terms in the last line were ignored in (12a) as negligible: they correspond to the effects of tariff changes that operate through differential price indices; they only affect the earnings channel if consumer base μ_j is correlated with skill intensity and if spending on imports varies across groups, neither of which happens much in our data. Finally, ignoring analogous negligible effects, the elasticity of the industry

size with respect to the lower skill premium, which enters σ_{macro} , is given by

$$\begin{aligned}
\eta_j^{\text{skill prem}} &= \text{Export share}_j \cdot (\xi_j - 1) (v_j - \bar{v}) + \text{Dom share}_j \cdot \{(\xi_j - 1) IP_j (v_j - \bar{v}) \\
&\quad + (\varepsilon_r - 1) ((1 - IP_j) (v_j - \bar{v}) - \mathbb{E}_{\text{Final}} [(1 - IP_j) (v_j - \bar{v}) | r]) \\
&\quad + (\rho - 1) (\mathbb{E}_{\text{Final}} [(1 - IP_j) (v_j - \bar{v}) | r] - \mathbb{E}_{\text{Final}} [(1 - IP_j) (v_j - \bar{v})]) \\
&\quad + (\psi_j - 1) \mathbb{E}_{\text{Final}} [(1 - IP_j) (v_j - \bar{v})] - \psi_j (\mu_j - \bar{\mu})\}.
\end{aligned} \tag{A15}$$

Proof of (13)–(14). With the approximation $\mathbb{E}_{VA} [\eta_j^{\text{skill prem}}] \cdot (\hat{w}_S - \hat{w}_U) \approx 0$, (9) and (11) imply (13a):

$$\begin{aligned}
\hat{w} &= \mathbb{E}_{VA} [\widehat{VA}_j] \\
&\approx \mathbb{E}_{VA} [\eta_{jc}^{\text{import}} \cdot \hat{\tau} + \eta_j^{\text{export}} \cdot (-\hat{\tau}^*) + \eta_j^{\text{avg wage}} \hat{w}] \\
&= \frac{\mathbb{E}_{VA} [\eta_j^{\text{import}}] \hat{\tau} + \mathbb{E}_{VA} [\eta_j^{\text{export}}] \cdot (-\hat{\tau}^*)}{1 - \mathbb{E}_{VA} [\eta_j^{\text{avg wage}}]}.
\end{aligned}$$

Moreover, (10) and (11) together imply (13b):

$$\begin{aligned}
\hat{w}_S - \hat{w}_U &= \frac{\Delta_{VA} [\widehat{VA}_j]}{\sigma_{\text{within}}} \\
&= \frac{\Delta_{VA} [\eta_{jc}^{\text{import}} \cdot \hat{\tau} + \eta_j^{\text{export}} \cdot (-\hat{\tau}^*) + \eta_j^{\text{avg wage}} \hat{w} - \eta_j^{\text{skill prem}} (\hat{w}_S - \hat{w}_U)]}{\sigma_{\text{within}}} \\
&= \frac{\Delta_{VA} [\eta_{jc}^{\text{import}} \cdot \hat{\tau} + \eta_j^{\text{export}} \cdot (-\hat{\tau}^*) + \eta_j^{\text{avg wage}} \hat{w}]}{\sigma_{\text{within}} + \Delta_{VA} [\eta_j^{\text{skill prem}}]}.
\end{aligned}$$

Without the approximation, the system of equations (9)–(11) attains a solution at

$$\begin{pmatrix} \hat{w} \\ \hat{w}_S - \hat{w}_U \end{pmatrix} = \begin{pmatrix} 1 - \mathbb{E}_{VA} [\eta_j^{\text{avg wage}}] & \mathbb{E}_{VA} [\eta_j^{\text{skill prem}}] \\ -\frac{\Delta_{VA} [\eta_j^{\text{avg wage}}]}{\sigma_{\text{within}}} & 1 + \frac{\Delta_{VA} [\eta_j^{\text{skill prem}}]}{\sigma_{\text{within}}} \end{pmatrix}^{-1} \cdot \begin{pmatrix} \mathbb{E}_{VA} [\eta_{jc}^{\text{import}}] \hat{\tau} + \mathbb{E}_{VA} [\eta_j^{\text{export}}] \cdot (-\hat{\tau}^*) \\ (\Delta_{VA} [\eta_{jc}^{\text{import}}] \hat{\tau} + \Delta_{VA} [\eta_j^{\text{export}}] \cdot (-\hat{\tau}^*)) / \sigma_{\text{within}} \end{pmatrix}.$$

Discussion of σ_{macro} . Recall that $\sigma_{\text{macro}} = \sigma_{\text{within}} + \Delta_{VA} [\eta_j^{\text{skill prem}}]$. The second term can be expressed as a cross-industry average, $\Delta_{VA} [\eta_j^{\text{skill prem}}] = \mathbb{E}_{VA} [\eta_j^{\text{skill prem}} \cdot \frac{v_j - \bar{v}}{\bar{v}(1 - \bar{v})}]$ (see analogous equation

(A30) in Theory Appendix A.5). Plugging this into (A15), we obtain

$$\begin{aligned} \sigma_{\text{macro}} &= (1 - \text{Segm}_{\text{prod}}) \bar{\sigma} + \omega_{\xi} \bar{\xi} + \omega_{\varepsilon} \bar{\varepsilon} + \omega_{\rho} \rho + \omega_{\psi} \bar{\psi} \\ &\quad - \Delta_{VA} [\text{Dom share}_j \cdot \psi_j (\mu_j - \bar{\mu})]. \end{aligned}$$

Here $\omega_{\xi} + \omega_{\varepsilon} + \omega_{\rho} + \omega_{\psi} = \text{Segm}_{\text{prod}}$, so the first line is a weighted average of elasticities in the model: σ_j , ξ_j , ε_r , ρ , and ψ_j , similar to Oberfield and Raval (2014).⁴² The weights correspond to the importance of different types of labor reallocation: $1 - \eta_{\text{prod}}$ is large when skill-intensities are relatively homogeneous across industries, which creates room for within-industry reallocation. The other terms capture different types of between-industry reallocation. For example, the weight on the trade elasticities (ω_{ξ}) is larger when the economy is more open on both import and export sides. The second line provides a segregation adjustment.

A.2 General Model

In this section we derive the average gains from trade policy, as well as the distributional effects through the expenditure and earnings channels in the general model, which allows for input-output linkages.

To characterize intermediate demand, we make a functional form assumption on the production function: it combines intermediate inputs from various industries with the composite output of labor inputs (which are the sources of value added) in the Cobb-Douglas way,

$$Q_{jH} = \left(F_j^{\text{VA}} \left(L_S^j, L_U^j \right) \right)^{1-\beta_j} \cdot \prod_{\ell} \left(Q_{\ell}^j \right)^{\beta_{\ell}^j},$$

where F_j^{VA} is a homogeneous of degree one function with local elasticity of substitution σ_j , $\beta_j = \sum_{\ell} \beta_{\ell}^j$ is the total cost share of intermediates, and matrix $\mathbf{B} = \left(\beta_{\ell}^j \right)$ is the input requirement (I-O) matrix. The rows of \mathbf{B} correspond to selling (upstream) industries ℓ , columns to buying (downstream) industries j , and elements measure the fraction of domestic industry j 's costs spent on inputs from industry ℓ . Q_{ℓ}^j is the quantity of the industry- ℓ composite commodity purchased by j , and it combines varieties from all countries in the same CES way as final consumers aggregate them. That is the standard proportionality condition that the BEA input-output table relies on.⁴³ The Cobb-Douglas assumption is only required for the earnings channel—as before, the expenditure channel results remain non-parametric.

As in Section 2, we proceed in two steps. We first characterize price changes conditionally on wage changes and solve for the average gains and the expenditure channel. Then we solve for changes in the industry size and link them to the growth of the skill premium.

⁴²For instance, $\omega_{\xi} = \mathbb{E}_{VA} \left[(1 - \text{Dom share}_j \cdot (1 - IP_j)) \frac{(v_j - \bar{v})^2}{\bar{v}(1-\bar{v})} \right] = \Delta_{VA} [(1 - \text{Dom share}_j \cdot (1 - IP_j)) (v_j - \bar{v})]$, and other weights are similarly obtained from $\Delta_{VA} \left[\eta_j^{\text{skill prem}} \right]$.

⁴³The proportionality condition is also standard in the literature (e.g. Caliendo and Parro 2015). The World Input-Output Database departs from it slightly by allowing for differences in import shares between final and intermediate consumers (but not across different types of each). However, it is more aggregated and has other limitations (Timmer et al. 2015).

Step 1. Price Changes. We show that industry-specific consumer (producer) price indices are determined by the *total* share of spending on imports (on imported intermediates), both direct and indirect. We use tildes to denote objects that account for upstream suppliers, and define the total share of imports from country c in consumption (\widetilde{IP}_{jc}) and in domestic production ($\widetilde{IP}_{jc}^{\text{Interm}}$) in an intuitive recursive way:

$$\widetilde{IP}_{jc} = IP_{jc} + (1 - IP_j) \cdot \widetilde{IP}_{jc}^{\text{Interm}}, \quad (\text{A16a})$$

$$\widetilde{IP}_{jc}^{\text{Interm}} = \sum_{\ell} \beta_{\ell}^j \widetilde{IP}_{jc}, \quad (\text{A16b})$$

with analogous notation for imports from a set of countries \mathbf{c} or from all foreign countries. [Tintelnot et al. \(2017\)](#) use similar definitions looking at the firm-to-firm input-output network. In matrix form, (A16a) solves as $\widetilde{IP}_c = \widetilde{\mathbf{B}} \cdot IP_c$ where $\widetilde{\mathbf{B}} = (\mathbf{I} - \text{diag}(1 - IP_j) \mathbf{B}')^{-1}$ is a Leontief-type inverse matrix.⁴⁴

By Shephard's lemma, producer price index satisfies

$$\hat{p}_{jH} = (1 - \beta_j) (\hat{w} + (v_j - \bar{v}) (\hat{w}_S - \hat{w}_U)) + \sum_{\ell} \beta_{\ell}^j \hat{p}_j.$$

And consumer price index combines domestic and foreign price changes:

$$\hat{p}_j = IP_{jc} \hat{\tau} + (1 - IP_j) \hat{p}_{jH}.$$

Combining these expressions, we obtain a recursive characterization for the consumer price index that parallels (A16a)–(A16b):

$$\begin{aligned} \hat{p}_j &= IP_{jc} \hat{\tau} + (1 - IP_j) \left((1 - \beta_j) (\hat{w} + (v_j - \bar{v}) (\hat{w}_S - \hat{w}_U)) + \sum_{\ell} \beta_{\ell}^j \hat{p}_j \right) \\ &= \widetilde{IP}_{jc} \hat{\tau} + \left(1 - \widetilde{IP}_j \right) (\hat{w} + (\tilde{v}_j - \bar{v}) (\hat{w}_S - \hat{w}_U)), \end{aligned} \quad (\text{A17})$$

where \tilde{v}_j is the average skill intensity of the domestic part of the supply chain leading to good j , which is defined in matrix form by $\left\{ (1 - \widetilde{IP}_j) \tilde{v}_j \right\} = \widetilde{\mathbf{B}} \cdot \left\{ (1 - \beta^j) (1 - IP_j) v_j \right\}$. Similarly for producer price index,

$$\hat{p}_{jH} = \widetilde{IP}_{jc}^{\text{Interm}} \hat{\tau} + \left(1 - \widetilde{IP}_j^{\text{Interm}} \right) (\hat{w} + (\tilde{v}_j - \bar{v}) (\hat{w}_S - \hat{w}_U)). \quad (\text{A18})$$

Expressions (A17) and (A18) generalize (6) and (5), respectively. They imply the expressions for the average gains and the expenditure channel that are analogous to (7) and (8), with tildes added.

Step 2. Wage Changes. The connection between the wage changes and differential growth of industries in Step 2a (equations (9) and (10)) holds in the general model.⁴⁵ To solve for the aver-

⁴⁴Multiplication of \mathbf{B}' by $\text{diag}(1 - IP_j)$ is the open-economy adjustment to the I-O table described by [Antràs et al. \(2012\)](#).

⁴⁵The proof goes through as long as the production function can be written as $Q_{jH} = F_j(F_j^{\text{VA}}(L_S^j, L_U^j), Q_1^j, \dots, Q_{\mathcal{J}}^j)$ for some F_j homogenous of degree one, so that substitution patterns between labor types are independent of the choice of

age wage and skill premium changes, it remains to generalize Step 2b, i.e. equations (12a)–(12c), by characterizing the changes in industry value added. We start from the product market clearing condition. Domestic output can be sold to domestic final and intermediate consumers, as well as to exports: $X_{jH} = X_{jH}^{\text{Final}} + X_{jH}^{\text{Interm}} + X_{jH}^{\text{Export}}$, where $X_{jH}^{\text{Interm}} = \sum_k X_{jH}^k$ measures total intermediate sales and k indexes domestic downstream industries, each buying X_{jH}^k from j .

To measure the contribution of different modes of selling to the total, we need to know the weights of each term in the total before the shock and to predict their changes after the shock. Regarding the former, the I-O table reports the share of exports *in output* and the share of final consumers and each downstream industry k *in absorption*; purchases of domestic varieties by different buyers are not reported directly. However, they can be computed using the proportionality condition. Specifically, we introduce the intermediate absorption matrix $\mathbf{D} = (\delta_j^k)$. Its rows (columns) correspond to the selling (buying) industries j (k), and typical element $\delta_j^k = X_{jH}^k / \text{Absorption}_j$ measures the share of industry j 's absorption (domestic spending on both domestic and foreign varieties) that is used as intermediate inputs to downstream industry k . While \mathbf{B} looks at the industry's suppliers, \mathbf{D} characterizes its buyers. By proportionality, shares δ_j^k can be applied to the domestic sales of *domestic* varieties, i.e. $X_{jH}^k / (X_{jH}^{\text{Final}} + X_{jH}^{\text{Interm}}) = \delta_j^k$. Therefore, the share of domestic output that goes to k equals $X_{jH}^k / X_{jH} = \text{Dom share}_j \cdot \delta_j^k$. Similarly, the share of domestic output that is sold to domestic final consumers is $\text{Dom share}_j \cdot (1 - \delta_j) \equiv \text{Dom final share}_j$, where $\delta_j = \sum_k \delta_j^k$ measures the share of final sales in absorption. As a result,

$$\hat{X}_{jH} = \text{Export share}_j \cdot \hat{X}_{jH}^{\text{Export}} + \text{Dom final share}_j \cdot \hat{X}_{jH}^{\text{Final}} + \text{Dom share}_j \cdot \sum_k \delta_j^k \hat{X}_{jH}^k. \quad (\text{A19})$$

The change in output on the left-hand side equals \widehat{VA}_j due to the Cobb-Douglas assumption. To characterize the change in intermediate sales \hat{X}_{jH}^k , we apply Cobb-Douglas again. The share of spending by industry k on *all* varieties of j is fixed, so $\hat{X}_j^k = \hat{X}_k$, but substitution between domestic and foreign varieties implies that domestic sales of j to k changes by $\hat{X}_{jH}^k = \hat{X}_k + (1 - \xi_j)(\hat{p}_{jH} - \hat{p}_j)$. Plugging these into (A18) yields a recursive characterization for \widehat{VA}_j :

$$\begin{aligned} \widehat{VA}_j &= \text{Export share}_j \cdot \hat{X}_{jH}^{\text{Export}} + \text{Dom final share}_j \cdot \hat{X}_{jH}^{\text{Final}} \\ &\quad + \text{Dom share}_j \cdot \left(\delta_j (1 - \xi_j) (\hat{p}_{jH} - \hat{p}_j) + \sum_k \delta_j^k \widehat{VA}_k \right). \end{aligned}$$

Denoting $\text{Interm share}_j = \text{Dom share}_j \cdot \delta_j$ and solving it in matrix form, we obtain

$$\begin{aligned} \widehat{VA} &= \tilde{\mathbf{D}} \cdot \left\{ \text{Export share}_j \cdot \hat{X}_{jH}^{\text{Export}} + \text{Dom final share}_j \cdot \hat{X}_{jH}^{\text{Final}} \right. \\ &\quad \left. + \text{Interm share}_j \cdot (1 - \xi_j) (\hat{p}_{jH} - \hat{p}_j) \right\}, \end{aligned} \quad (\text{A20})$$

where $\tilde{\mathbf{D}} = (\mathbf{I} - \text{diag}(\text{Dom share}_j) \mathbf{D})^{-1}$ is the Leontief inverse corresponding to \mathbf{D} . Three terms in intermediate inputs and σ_j is well-defined. The Cobb-Douglas assumption is sufficient but not necessary.

(A20) correspond to direct changes in export demand, domestic final demand, and competition with foreign varieties in intermediate markets. Pre-multiplication by $\tilde{\mathbf{D}}$ makes the *I-O adjustment* to account for the propagation of shocks from downstream industries up through changes in intermediate demand; algebraically, (A20) is the sum of direct value added changes in the industry itself, its intermediate customers, their customers, etc. For example, elements of $(\tilde{\mathbf{D}} \cdot \text{Export share})$ are shares of domestic output that is exported either directly or indirectly by selling to domestic downstream industries that export. Similarly, elements of $(\tilde{\mathbf{D}} \cdot \text{Dom final share})$ are the complementary shares of output ultimately sold to domestic consumers.

Expressions (A11) and (A12) for changes in export and domestic final demand follow from the corresponding demand systems and extend to the general model with no change. We plug in consumer and producer price indices from (A17) and (A18) and collect terms at $\hat{\tau}$, $\hat{\tau}^*$, \hat{w} , and $\hat{w}_S - \hat{w}_U$ to arrive at (11), where industry size responses are characterized by the expressions we present in order.⁴⁶ The elasticity with respect to import tariffs (generalization of (12a)) combines the import competition, substitution, and income effects with a new effect of cheaper intermediate inputs:⁴⁷

$$\eta_j^{\text{import}} = \text{Import comp effect}_j - \text{Int.Input effect}_j + \text{Substitution effect}_j + \text{Income effect}_j. \quad (\text{A21a})$$

Here the import competition effect is like (12a) before, but it applies to both final and intermediate domestic buyers and is I-O adjusted:

$$\text{Import comp effect} = \tilde{\mathbf{D}} \cdot \{(\xi_j - 1) IP_{jc} \cdot \text{Dom share}_j\}. \quad (\text{A21b})$$

This effect can be partially offset by cheaper intermediate inputs that make domestic varieties more competitive relative to the foreign ones (and thus to the industry average). This new mechanism is captured by

$$\begin{aligned} \text{Int.Input effect}_j &= \tilde{\mathbf{D}} \cdot \left\{ (\xi_j - 1) \left(\tilde{IP}_{jc}^{\text{Interm}} - \tilde{IP}_{jc}^{\text{Interm}} (1 - IP_j) \right) \right\} \\ &= \tilde{\mathbf{D}} \cdot \left\{ (\xi_j - 1) \tilde{IP}_{jc}^{\text{Interm}} \cdot IP_j \right\}. \end{aligned} \quad (\text{A21c})$$

Finally, substitution and income effects are similar to the model in Section 2, but based on the total

⁴⁶Details of the algebra are available from the authors upon request.

⁴⁷This ignores negligible terms analogous to those discussed in Theory Appendix A.1.

reduction of consumer prices (both direct and indirect) and again I-O adjusted:

$$\begin{aligned} \text{Substitution effect}_j = \tilde{\mathbf{D}} \cdot \left\{ \left[(\varepsilon_r - 1) \left(\mathbb{E}_{\text{Final}} \left[\widetilde{IP}_{jc} \mid r \right] - \widetilde{IP}_{jc} \right) \right. \right. \\ \left. \left. + (\rho - 1) \left(\mathbb{E}_{\text{Final}} \left[\widetilde{IP}_{jc} \right] - \mathbb{E}_{\text{Final}} \left[\widetilde{IP}_{jc} \mid r \right] \right) \right] \cdot \text{Dom final share}_j \right\}. \end{aligned} \quad (\text{A21d})$$

$$\begin{aligned} \text{Income effect}_j = \tilde{\mathbf{D}} \cdot \left\{ -(\psi_j - 1) \cdot \text{Dom final share}_j \right\} \cdot \mathbb{E}_{\text{Final}} \left[\widetilde{IP}_{jc} \right] \\ \equiv -(\bar{\psi}_j - 1) \cdot \left(\tilde{\mathbf{D}} \cdot \text{Dom final share}_j \right) \cdot \mathbb{E}_{\text{Final}} \left[\widetilde{IP}_{jc} \right]. \end{aligned} \quad (\text{A21e})$$

The last line represents income effects in terms of the weighted average income elasticity $\bar{\psi}_j$ that combines the income elasticities of the varieties produced by the industry and its downstream buyers (“I-O-adjusted income elasticity”)

The responses of industry size to the lower export tariff and to higher domestic average wage are similar to (12b)–(12c) but I-O adjusted. In particular, the export effect includes exports in downstream industries:

$$\eta_j^{\text{export}} = \tilde{\mathbf{D}} \cdot \left\{ (\xi_j - 1) \text{Export share}_j \right\}, \quad (\text{A22})$$

$$\eta^{\text{avg wage}} = \tilde{\mathbf{D}} \cdot \text{Dom final share} - \eta^{\text{import}} - \eta^{\text{export}}. \quad (\text{A23})$$

The generalization of (A15) for $\eta_j^{\text{skill prem}}$ is obtained analogously (and not necessary for our calibration, as we calibrate σ_{macro} directly). This concludes Step 2b. Step 2c is unchanged, and equations (13)–(14) characterize the changes in the average wage and the skill premium.

A.3 Skill-Biased Import Competition

Our data do not allow us to observe which domestic firms face more import competition within an industry. Yet, if these firms have lower skill intensity than an average firm in the industry (e.g. Bernard et al. 2006), our measure of differential exposure to import competition, based on the industry import penetration, would be biased. Here we address this issue by assuming that the composition of marginal domestic workers displaced by import competition is known. Specifically, using the insight from Borjas et al. (1997), we will equate it to the skill mix of the industry in the past—in 2000 or in 1990 in our estimation with the idea that foreign varieties, particularly those from developing countries, are more similar to the older varieties produced in the U.S.⁴⁸

We embed this idea in our theoretical framework in the following way. Assume that each industry consists of two segments: traditional segment A and high-tech segment B. Skill intensity (the college payroll share) of segment A is v'_j , and we assume it is observable; the fraction of this segment in the industry output is denoted A_j , which is not observed. We do not make restrictions on the skill composition of segment B. We examine the case where all imports in the industry are concentrated in segment A,

⁴⁸Note that it does not matter how skill-intensive the production process is abroad. The relevant skill intensity is that of domestic varieties competing with foreign ones.

while B is completely insulated from competition with foreign varieties. This implies that the marginal mix of workers affected by trade has skill intensity v' . Besides differences in import penetration and skill intensity, these two segments are identical: they have the same share and composition of intermediate inputs, the same export share, etc. Consumers view composite products of A and B as two different industries with the same taste parameters.

This setup implies that all theoretical results of the paper go through, but there is aggregation bias: we need to measure the differential exposure to trade at the level of segments, while the data do not have that level of detail. However, the exposure of each group to exports, imported inputs, and income effects is unchanged because segments A and B are identical in those respects. We will now show that the knowledge of v' is sufficient to measure the differential exposure to imports.

We first establish that import penetration from some foreign country c within segment A equals $IP_{jA,c} = IP_{jc} / (IP_j + A_j(1 - IP_j))$. Indeed, normalizing the industry absorption to one for brevity, IP_j is the total value of imports in the industry, and therefore in segment A, while the denominator is the segment's absorption, which consists of all imports as well as share A_j of the industry's output purchased domestically, $1 - IP_j$. Import penetration in B is zero by construction.

Before measuring the exposure to import competition by worker type, we note that the average exposure equals $IP_{jc} \cdot \frac{A_j}{IP_j + A_j(1 - IP_j)} = IP_{jc} / \left(1 + \frac{1 - A_j}{A_j} IP_j\right)$, which is below IP_{jc} . By allowing for heterogeneity of import penetration within the industry, and therefore for specialization in different segments across countries, we reduced the effect of import competition even if $v'_j = v_j$. For the same reason the payroll-weighted average import penetration was found to be small in Section 6.2. To focus on the skill bias of import competition, we assume that either segment A is sufficiently large relative to segment B or import penetration is sufficiently low, so $\frac{1 - A_j}{A_j} \cdot IP_j \ll 1$, and the average exposure to imports is unaffected by having two segments per se.

Given that, the average exposure of skilled workers to imports in the industry equals the product of the payroll share of segment A for these workers and the import penetration in A:

$$\frac{A_j v'_j}{v_j} \cdot IP_{jA,c} = \frac{v'_j}{v_j} \cdot IP_{jc} \cdot \frac{A_j}{IP_j + A_j(1 - IP_j)} \approx \frac{v'_j}{v_j} \cdot IP_{jc}. \quad (\text{A24a})$$

Similarly, the exposure of unskilled workers equals

$$\frac{A_j(1 - v'_j)}{1 - v_j} \cdot IP_{jA,c} \approx \frac{1 - v'_j}{1 - v_j} \cdot IP_{jc}. \quad (\text{A24b})$$

Equations (A24a)–(A24b) present a very simple result: to measure the differential exposure in presence of the skill-bias of import competition, one needs to adjust exposure of the skilled group up by a factor v'_j/v_j , the exposure of the unskilled group down by $(1 - v'_j)/(1 - v_j)$, and the knowledge of the shares of segments is not required as long as segmentation of imports within the industry does not change the average exposure. Since we assume that the two segments are identical in other respects, including the

types of downstream domestic firms they sell to, we use the overall import penetration in downstream industries for I-O adjustments.

A.4 Roy Model

In this section we extend the model to allow for imperfect reallocation of labor across industries and for inequality of wages within skill groups. We use the model to establish two results. First, while trade generates winners and losers within each group, its only effect on nominal income inequality occurs between groups, by changing the average skill premium.⁴⁹ Second, changes in the average skill premium are still determined by the differential growth of industries employing the two groups via equation (10); the only difference is the expression for σ_{within} .

These results have limitations. First, they rely on commonly used but restrictive Roy selection forces. Second, we make a further assumption that the Fréchet parameter that determines the elasticity of industry labor supply is the same for both groups. Finally, these results do not imply that the model calibration from Section 7 goes through without changes, because prices, and therefore industry sizes, may change differently than in the baseline model. Yet, this extension suggests that our baseline model may capture some of the most important forces of the earnings channel.

The extension we consider is in the spirit of Galle et al. (2017) and Lee (2016), generalized to allow for imperfect substitutability between the two types of labor. As in Section 2, σ_j denotes the elasticity of substitution for the value-added production function $F_j^{\text{VA}}(E_S^j, E_U^j)$, except now E_i^j is the number of *efficiency units* of labor of type i employed by industry j . Each agent of type i draws a set of productivity parameters $z = (z_j)_{j=1}^J$ i.i.d. from the Fréchet distribution with shape parameter $\theta > 1$ and scale (productivity) parameter T_{ij} that is unaffected by trade. The shape parameter determines the elasticity of industry labor supply. A high value of θ implies that productivity is less dispersed, and therefore it is easy to switch across industries, while $\theta \rightarrow 1$ is equivalent to the case of no labor mobility (Galle et al. 2017). As mentioned above, we assume for tractability that θ is the same across types. We interpret w_i^j as the per-efficiency-unit wage, so the total earnings of a given worker equal $w_i^j z_j$.

A standard implication of the Fréchet functional form is that, due to equilibrium selection, the distribution of observed wages of type i is the same in all industries. Specifically, it is Fréchet with the scale parameter

$$\Phi_i = \left(\sum_j T_{ij} (w_i^j)^\theta \right)^{1/\theta} \quad (\text{A25})$$

and with mean $\kappa \Phi_i$, for $\kappa = \Gamma(1 - \frac{1}{\theta})$. As a result, out of the three potential types of wage inequality in this model—that across skill groups, across industries within skill, and within industry-skill group cells—which can be isolated with the standard Theil decomposition, only the first one is endogenously

⁴⁹It is instructive to note that the magnitudes of income changes for typical winners and losers may be large, potentially dwarfing the skill-premium changes. Yet, because those winners and losers are ex ante similar in terms of income, the shape of the income distribution in each group does not change.

determined. The second one is absent in equilibrium and the third one is exogenously given by θ .

We can therefore focus our attention on the average skill premium Φ_S/Φ_U , which fully characterizes the between inequality. Below we prove that in this model equation (10) characterizes the change in the skill premium given

$$\sigma_{\text{within}} = 1 + \mathbb{E}_{VA} \left[\frac{v_j(1-v_j)}{\bar{v}(1-\bar{v})} \cdot \frac{(\theta-1)(\sigma_j-1)}{\theta-1+\sigma_j} \right].$$

Two extreme cases are interesting here. When $\theta \rightarrow \infty$, which corresponds to free labor mobility, σ_{within} converges to the value from the baseline model. When $\theta \rightarrow 1$, interpreted as no mobility (i.e., specific factors in each industry), $\sigma_{\text{within}} \rightarrow 1$, which implies that $\hat{\Phi}_S - \hat{\Phi}_U = \Delta_{VA} [\widehat{VA}_j]$. This result is intuitive: with specific factors, the output quantity cannot change in any industry, and all industry wages grow proportionately to the dollar value of that output. Therefore, the average wage growth of a skill group equals the average growth of the employing industries.

Proof of (10) in the Roy model. By the well-known property of Fréchet, the share of employment of type i that comes from industry j equals the share of payroll and is given by $e_i^j = T_{ij} (w_i^j)^\theta / \Phi_i^\theta$. Therefore, the total earnings of group i in industry j is given by

$$\begin{aligned} w_i^j E_i^j &= \kappa \Phi_i e_i^j L_i \\ &= \kappa T_{ij} (w_i^j)^\theta \Phi_i^{1-\theta} L_i, \end{aligned} \tag{A26}$$

or, in log-differences, $\widehat{w_i^j E_i^j} = \theta \hat{w}_i^j + (1-\theta) \hat{\Phi}_i$.

Using $v_j/(1-v_j) = w_S^j E_S^j / w_U^j E_U^j$, we obtain

$$\left(\widehat{\frac{v_j}{1-v_j}} \right) = \theta (\hat{w}_S^j - \hat{w}_U^j) + (1-\theta) (\hat{\Phi}_S - \hat{\Phi}_U).$$

By definition of σ_j , the left-hand side can also be expressed as

$$\left(\widehat{\frac{v_j}{1-v_j}} \right) = (1-\sigma_j) (\hat{w}_S^j - \hat{w}_U^j).$$

Combining the two characterizations yields:

$$\hat{w}_S^j - \hat{w}_U^j = \frac{\theta-1}{\theta-1+\sigma_j} (\hat{\Phi}_S - \hat{\Phi}_U).$$

Using $\kappa \Phi_S L_S = \sum_j VA_j v_j$ and $\kappa \Phi_U L_U = \sum_j VA_j (1-v_j)$ and proceeding similarly to the proof in

Theory Appendix A.1, we get the desired result:

$$\begin{aligned}
\hat{\Phi}_S - \hat{\Phi}_U &= \sum_j (e_S^j - e_U^j) \widehat{VA}_j + \sum_j (e_S^j \hat{v}_j - e_U^j \widehat{1 - v_j}) \\
&= \Delta_{VA} [\widehat{VA}_j] + \sum_j (1 - \sigma_j) (e_S^j (1 - v_j) + e_U^j v_j) (\hat{w}_S^j - \hat{w}_U^j) \\
&= \Delta_{VA} [\widehat{VA}_j] + \mathbb{E}_{VA} \left[(1 - \sigma_j) \frac{v_j (1 - v_j)}{\bar{v} (1 - \bar{v})} \cdot \frac{\theta - 1}{\theta - 1 + \sigma_j} \right] (\hat{\Phi}_S - \hat{\Phi}_U) \\
&= \frac{\Delta_{VA} [\widehat{VA}_j]}{\sigma_{\text{within}}}.
\end{aligned}$$

A.5 Two Decompositions

To empirically investigate the differences in spending on imports ($\Delta_{\text{Final}}[IP_{jc}]$) and the differences in exposure to the labor market effects of trade through various channels ($\Delta_{VA}[\cdot]$), we exploit two decompositions established in this section.

First, differential effects can be represented as a sum of the components arising “between” and “within” more aggregated groups of products (for instance, sectors). Using the expenditure side notation,

$$\Delta_{\text{Final}}[IP_{jc}] = \underbrace{\sum_g (s_g^S - s_g^U) IP_{gc}}_{\equiv \Delta_{\text{Final}}^{\text{between}}[IP_{jc}]} + \underbrace{\sum_j (s_j^S - s_j^U) (IP_{jc} - IP_{gc})}_{\equiv \Delta_{\text{Final}}^{\text{within}}[IP_{jc}]} . \quad (\text{A27})$$

In these expressions g indexes product groups, s_g^i is the share of spending of type i on all products in group g , and IP_{gc} is the average import share for all products in group g , with total final expenditures weights. The “between” component ignores compositional differences within product groups, while the “within” component isolates those.

Second, we note that there is a convenient way of visualizing the main patterns in the data. It is intuitive that the share of spending on imports is higher for the skilled than unskilled *consumers* (in the agent space) if and only if *industries* that sell relatively more to the skilled group have higher import content (in the product space). We formalize this idea by defining consumer base μ_j as the fraction of industry j ’s domestic final sales that goes to the skilled group, as in Section A.1. . Then the difference in spending on imports can be represented as the slope of the regression of import penetration on the consumer base, β_{cons} , rescaled by the *consumption segmentation index*, $\text{Segm}_{\text{cons}}$, which measures the difference between consumption baskets of the two types in a model-consistent way:⁵⁰

$$\Delta_{\text{Final}}[IP_{jc}] = \underbrace{\frac{\text{Cov}[\mu_j, IP_{jc}]}{\text{Var}[\mu_j]}}_{\equiv \beta_{\text{cons}}} \cdot \underbrace{\frac{\text{Var}[\mu_j]}{\bar{\mu}(1 - \bar{\mu})}}_{\equiv \text{Segm}_{\text{cons}}} , \quad (\text{A28})$$

⁵⁰The final consumption-weighted average $\bar{\mu}$ represents the fraction of the skilled population in total expenditures. If $\zeta_S = \zeta_U$, it also equals the average skill intensity. Consumption segmentation index is related to, but conceptually distinct from, a commonly used dissimilarity index (Duncan and Duncan 1955).

Segmentation equals zero when all industries have the same mix of final consumers and attains the maximum value of one when each industry sells only to one group. Decomposition (A28) shows that skilled consumers spend more on imports when segmentation is sufficiently high and import shares are higher in industries with skilled consumers. The regression slope can be visualized using scatterplots and other standard tools.

Analogous decompositions hold on the earnings side, with three differences: industries are weighted by value added instead of final consumption, spending shares are replaced with payroll shares e_i^j , and consumer base μ_j is replaced by the skill intensity v_j . The counterpart to $\text{Segm}_{\text{cons}}$ is the production segmentation index $\text{Segm}_{\text{prod}} = \text{Var}[v_j] / \bar{v}(1 - \bar{v})$, which measures the heterogeneity of industries by skill intensity. Oberfeld and Raval (2014) consider an equivalent index based on capital intensity, which they call the heterogeneity index.

Proofs. The within-between decomposition is straightforward. By definition of the spending share of the group of products, $s_g^i = \sum_{j \in g} s_j^i$. This implies

$$\Delta_{\text{Final}}^{\text{between}} [IP_{\mathbf{c}}] = \sum_j (s_j^S - s_j^U) IP_{g\mathbf{c}}.$$

Adding it up with $\Delta_{\text{Final}}^{\text{within}} [IP_{\mathbf{c}}]$, one immediately gets $\Delta_{\text{Final}} [IP_{\mathbf{c}}]$, as required.

To establish decomposition (A28), note that the share of an industry in the college graduates' spending can be represented in the following way:

$$\begin{aligned} s_j^S &= \frac{X_j^S}{X_S} \\ &= \frac{X_j^S + X_j^U}{X_S + X_U} \cdot \frac{X_j^S / (X_j^S + X_j^U)}{X_S / (X_S + X_U)} \\ &= s_j^{\text{Final}} \cdot \frac{\mu_j}{\bar{\mu}}. \end{aligned} \tag{A29a}$$

This expression implies, for instance, that industry j is overrepresented in consumption of the skilled group ($s_j^S > s_j^{\text{Final}}$) if and only if $\mu_j > \bar{\mu}$. Similarly for the unskilled group,

$$s_j^U = s_j^{\text{Final}} \cdot \frac{1 - \mu_j}{1 - \bar{\mu}}. \tag{A29b}$$

Plugging (A29a) and (A29b) into the differential spending formula yields a representation of differential spending as a rescaled covariance between import penetration and the consumer base across

industries:

$$\begin{aligned}
\Delta_{\text{Final}} [IP_{\mathbf{c}}] &= \sum_j (s_j^S - s_j^U) IP_{\mathbf{c}} \\
&= \sum_j s_j^{\text{Final}} \left(\frac{\mu_j}{\bar{\mu}} - \frac{1 - \mu_j}{1 - \bar{\mu}} \right) IP_{j\mathbf{c}} \\
&= \mathbb{E}_{\text{Final}} \left[\frac{\mu_j - \bar{\mu}}{\bar{\mu}(1 - \bar{\mu})} IP_{j\mathbf{c}} \right] \\
&= \frac{\text{Cov} [\mu_j, IP_{j\mathbf{c}}]}{\bar{\mu}(1 - \bar{\mu})}, \tag{A30}
\end{aligned}$$

where covariance is weighted by total final consumption. Multiplying and dividing by $\text{Var} [\mu_j]$, we arrive at (A28).

B Data Replication Appendix

B.1 Consumer Expenditure Survey

The CEX is a stratified household survey conducted by the U.S. Bureau of Labor Statistics that measures the universe of personal spending with over 600 detailed product categories. The CEX consists of two separate parts, the interview and diary surveys, which we use in combination. Quarterly interviews cover the complete range of expenditures, whereas diaries focus on some categories, such as food and clothing, in much greater detail. The interview panel include around 6,900 households per quarter, each surveyed for four consecutive quarters. Diaries are collected for roughly the same number of distinct households per year but capture only two weeks of consumption. We select categories of spending (UCC) from both surveys according to the Integrated Stub file provided by the CEX, so that they cover all categories without double-counting.

The key advantage of CEX is that consumption structure can be measured separately for different groups of households. We split panelists by education of the household’s reference person answering the interview (variable `EDUC_REF`), defining college education as bachelor’s degree or higher, but the results are nearly identical if we use education of both male and female heads of the household. We also split households by bins of household income before tax. To do so, we use variable `FINCBTXM` in the interview survey and `FINCBEFX` in the diary survey. Eleven income bins are defined by the following cutoffs (in \$000): 10, 20, 30, 40, 50, 60, 75, 90, 110, and 150.

To increase the sample size, we combine data from 2006–2008. We drop all households with reported income below \$5,000 because of concerns about misreporting and temporary unemployment. Our final interview sample includes 32,668 unique households with average annualized spending of \$34,605, while the diary sample has 16,901 households spending \$13,145 per household per year.

Expenditure on housing services requires special treatment. The range of CEX spending categories includes rents and mortgage interest, but not the mortgage principal payments. However, an addendum section of the interview survey provides information on the self-reported rental value of owned property. In our static setup that is the closest analog to annual expenditures on housing for home-owners, so we add imputed rents to the set of UCC we consider. [Aguiar and Bils \(2015\)](#) follow a similar approach.

We build a manual concordance from 660 CEX consumption categories into 170 I-O industries. We thank James O’Brien for providing us with the concordance between CEX interview categories and the 2012 version of NAICS from [Levinson and O’Brien \(2017\)](#). We use this concordance, converted into 2007 I-O codes, as a starting point. We manually extend it to diary categories as well as missing interview ones. The concordance is many-to-one, with a few exceptions where we allocate CEX consumption by each group equally across the corresponding I-O codes. In most cases, our concordance is consistent with, but much finer than, the concordance from CEX to NIPA personal consumption expenditure categories provided by the BLS and used by [Buera et al. \(2015\)](#) and [Jaimovich et al. \(2015\)](#), among others.

B.2 BEA Input-Output Table

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

We classify all industries into goods or services. Manufacturing, agriculture, and mining are classified into goods, while all other industries into services. Construction is sometimes viewed as a good-producing industry (Comin et al. 2016) and sometimes as a service industry (Cravino and Sotelo 2018). We treat construction as an industry ultimately providing shelter for households and businesses, therefore we classify it into services. Goods and services are further classified into 24 and 15 subsectors, corresponding to three-digit I-O codes and two-digit NAICS codes, respectively. We assign Management and Administrative services (NAICS industries 55 and 56) to the subsector of Professional, Scientific, and Technical Services (code 54).

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

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

We address these issues by constructing an “augmented” I-O table which yields correct measures of exposure to trade for both consumers and producers. To do so, we create two versions for each industry. The “producer version” hires primary factors and purchases intermediate inputs, produces

output, exports, and gets imported. Then, the entire value of domestic absorption is sold to the “purchaser version” of that industry, which also buys distribution services from the corresponding industries and sells the combined outcome to final consumers and to producer versions of industries using its output as intermediate input. Only the distribution margin of exporting (e.g., wholesaling of exported goods) is recorded as direct exports of the distribution industries. All the formulas of our model with I-O linkages apply to this I-O table. Although import penetration and export shares are zero in purchaser industries, value added is zero there as well, so the earnings-side patterns can be computed using the augmented table. Similarly, the relevant measure of import content is computed in purchaser industries, which is indeed where all final consumption is concentrated.

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

We finally note that in constructing measures of direct and indirect import content, we do not classify goods into final and intermediate ones, which is problematic because many goods are used in both ways. Instead we rely on the input-output table to decompose the *use* of the same products as final or intermediate.

B.3 Linked Nielsen-Census Dataset

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

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

We use three data sources on the Census side. Business Register, or SSEL, is the comprehensive list

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

The Economic Census is the survey of all business establishments in the U.S. It is conducted by the Census Bureau in years that end with 2 or 7, and participation is required by law. The content of the questionnaire varies across sectors and industries but all of them include questions on the total revenue. We primarily use Censuses of Manufactures, Wholesale, and Retail. Establishments in Services, Finance, and Utilities are also part of our Economic Census sample, but they are rarely matched to Nielsen.

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

Sample Construction. We predict total sales of each Nielsen barcode by applying projection weights provided by Nielsen to the purchases by each household and, using the GS1 crosswalk, aggregate them to firms and firm-module cells. We classify households into college- and non-college by using education of both male and female heads. If they are both present but only one has college degree, we attribute half of the purchases to each education group. Income is reported in 16 discrete bins, and we use their midpoints.⁵¹ Income is reported with a two-year lag, so we use the value from two years after, whenever available.

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

We then compute import shares for each Census firm. The numerator is total imports from LFTTD. To measure the total firm output in the denominator, we aggregate revenue of all establishments belonging to the firm. However, this creates double-counting if a manufacturing company ships its products to its own wholesalers or retailers and then sells them. Therefore, we only count the total revenue in the largest 2-digit NAICS sector in which the firm operates, although the results are not substantially different without this correction. We drop firms for which imports exceed 200% of annual sales, indicating an imperfect match between LFTTD and the Census.

Finally, we merge name and addresses in GS1 with the Census firms—a procedure we describe next. Once done, we implement a consistency filter. Some firms, particularly large ones, span many industries, so their scope may not be covered well by the set of products covered by Nielsen. As a result, the overall

⁵¹The cutoffs in \$000 are: 5, 8, 10, 12, 15, 20, 25, 30, 35, 40, 45, 50, 60, 70, and 100. In some years, the top-income group is decomposed further, but we use a consistent classification. We assign the top-income group the value of \$140,000, based on the average income in the years when we have more detailed data.

importing behavior may be a very bad proxy for the set of products covered by Nielsen. We therefore require that Nielsen sales of a firm are within the range of 1% and 300% of the Census sales. Although still wide, this range excludes strongest violations of consistency in both directions and makes our results robust to using the square-root of Nielsen or Census sales as weights.

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

Pre-processing. We use the algorithms from the `reclink2` package from [Wasi and Flaaen \(2015\)](#), with minor modifications. For company names, the `stnd_compname` command removes special symbols, makes standard substitutions (e.g., INTL to International), and isolates the entity type (e.g., INC) into a separate variable. Pre-processing of addresses is particularly important. The `stnd_address` command parses them into several parts: the main address variable (where special symbols are removed, street types are converted to their abbreviations, e.g., Street into ST, etc.), as well as the post office box, unit (e.g. SUITE 1400), and building numbers, if present. We implement an important addition to this parsing procedure by also extracting the house number from the address. We define it as the number at the beginning of the address or, if the address starts with a letter, the largest number in the address.⁵²

Matching Algorithm. The SSEL consists of records of three types: multi-unit (one per establishment for firms with multiple establishments), “submaster” (one per tax identifier of a multi-unit firm, created for consistency with the IRS), and single-unit. We give priority to multi-unit and submaster records by first attempting to match GS1 firms to them. For GS1 firms that are still not merged, we try matching to single-unit firms that are part of the LBD (the Longitudinal Business Database, which links SSEL records across years). The lowest priority is given to single-unit firms outside of the LBD.⁵³

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

⁵²Extracting the largest number is inspired by the the addresses of foreign firms are treated in the LFTTD (see [Kamal and Monarch 2016](#)). With fuzzy matching, matching on the house number ensures that buildings like 47 Main St. and 49 Main St. are distinguished. It is also very useful for parts of Wisconsin and Illinois which use alphanumeric addresses, e.g. “W190 N10768 Commerce Cir, Germantown, WI.”

⁵³One SSEL record may list up to two addresses per establishment (physical and mailing) and sometimes specifies two zipcodes (one reported and one inferred automatically based on the rest of the address). We use all available versions of the address to increase the probability of the match.

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

Table [A14](#) lists the rules. The two strictest rule require a non-missing match is required for the 9-digit zipcode (ZIP+4). Although available only for some firms, it generally identifies the building or a post box precisely. The first rule additionally requires an exact (possibly missing) match for the firm name, house number, address, PO Box, unit, and building, standardized as previously described, while the second rule only requires an exact match on the house number, while the other variables are matched in a fuzzy way. The least restrictive seventh rule requires exact matches on the firm name, its entity type, and state, still delivering high quality of matches for the records that have not been matched using stricter rules.

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

Match Statistics. Panel (a) of Table [A15](#) shows that the majority of Nielsen firms, excluding tiny ones, is matched, covering over 83% of total Nielsen sales.⁵⁴ In 2007, there were 26,900 Nielsen firms, and elimination of the tiny ones leaves us with 11,000 without any significant loss in total projected sales. Out of them we are able to find a Census match in the same year of the Census Business Register for 7,600, while using names and addresses from other years adds another 600 firms, making it 8,200 total. Although all firms are supposed to fill out Census forms, not all of them do, so we find 7,200 Nielsen firms in at least one of the Censuses, and of them 6,100 pass the consistency filter. Although there are a few cases where we find two Census matches for the same Nielsen firms, the number of Nielsen firms with single matches is the same 6,100 after rounding. Statistics are similar for 2012, increasing the sample size to 12,700 firm-years.

Panel (b) of Table [A15](#) shows merging statistics starting from Census firms. Since Nielsen only covers consumer packaged goods, we do not expect a high match rate in most industries. However, Nielsen coverage is strongest for food, alcohol, and tobacco. This panel starts from all 51,500 firms in the Census of Manufactures in the corresponding NAICS code 312. Out of them, 8,900 (or 17.3%) are merged to any Nielsen firm, including the tiny ones, and the merged ones account for 79% of the total sales. After dropping small Nielsen firms and implementing the consistency filter, we match only 9.3% of the firm count

⁵⁴The match rate is above 83% of sales for food and health and household products, but a bit worse for general merchandize, at 76%.

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

Table A16 shows that multi-establishment firms are a minority in the matched sample (29%), but they cover 93% of sales. Within both multi- and single-establishment matched firms, the strictest matching rule 1 captures the largest share of firms, but all rules contribute to the sample.

Table A17 shows the fractions of firms operating in different sectors, defined by their 2-digit NAICS codes, in the sample.⁵⁵ The manufacturing sector constitutes the largest fraction of the sample (57.2% with square-root weighting), followed by wholesaling (29.0%) and retailing (8.7%). The smaller share of retailers is in part determined by their large average sales, which imply that the square-root weighting scheme reduces their importance. At the same time, it is important to understand that most products sold by retailers are registered by other firms. We discuss below examples of products showing that this is true even for products manufactured for and distributed exclusively by Walmart. Among the 3-digit NAICS codes, Food Manufacturing and Nondurable Goods Wholesalers are the most prevalent ones, followed by Chemical Manufacturing (which includes soap, shampoos, etc.) and Beverage and Tobacco Manufacturing.

The last column of Table A17 presents a nice test on the quality of the match. Nielsen data allow us to identify products that are branded by the retail chain that sells them (“private label brands”). We find that over 99% sales of barcodes registered by food and beverage stores, according to their main NAICS code in the Economic Census, are private label brands. For comparison, this share is only 7.9% for wholesalers and mere 1.2% for manufacturers.

Table A18 examines how representative the matched sample is. Panel (a) compares firms in Nielsen, excluding tiny ones, that found a match to those that did not. Median firms in the merged sample have about twice as large Nielsen sales relative to the firms that did not find a match. Matched firms also sell to slightly, but statistically significantly, poorer and less educated consumers. For example, 29.1% of sales of matched firms is to college graduates, as opposed to 30.7% for firms that we did not match. However, these differences can largely be explained by the size difference; they are reduced when controlling for a quadratic term in log Nielsen sales. Panel (b) provides evidence on sample selection for the firms in the Census of Manufactures producing food, alcohol, and tobacco. Again, merged firms are much larger, with median sales of \$13.3 million, payroll of \$1.9 million and 54 employees, as opposed to \$606,000 sales, \$113,000 payroll and 4 employees for a median Census firm that we did not merge. Comparing these sets of firms by skill intensity (the payroll share of non-production workers) does not reveal statistically or economically significant differences.

Examples. A few examples illustrate the way in which our Nielsen-Census linked dataset labels products as domestic, imported, or as using imported intermediate inputs. We visited a Walmart store and photographed a sample of products, which we identify as domestic and imported by looking at their

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

labels. Then, we identified these products in the GS1 database using their barcodes and searched for the information about the firms that registered them on the Internet. Figure A9 shows pictures of five products that illustrate well different situations we observed.⁵⁶

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

The three other products on Figure A9 are all imported. The bed sheets in Panel (c) belong to the same brand as the plates in (b), they are distributed by Walmart, but their label indicates “Made in China”. In GS1, we see that their barcode was registered by Jiangsu Royal Home USA, Inc. Internet sources indicate that this firm belongs to the NAICS code 423220 “Home furnishing merchant wholesalers” and imports its products from China. Our Nielsen-Census linked dataset will therefore label this product as imported.

The plates in Panel (d), also made in China, are registered by First Design Global, Inc, which (again, according to Internet search) is a U.S.-based manufacturing firm but imports tableware and kitchenware from China. We will therefore attribute these plates partially to imports, using as a proxy the ratio of imports to total sales for this firm. This proxy does not bias our estimates of the expenditure channel if there is no systematic correlation between import content and buyer characteristics within firms.

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

B.4 Datasets or Motor Vehicles

Linked CEX-Ward’s Dataset. To measure purchases of motor vehicles by consumer group, we use the OVB file (“Owned Vehicles Detailed Questions”) from the CEX Interview Survey, which asks respondents to provide information about all vehicles they own, including the brand, whether the vehicle was purchased new or used, and in some cases the price. The respondents are asked to list all types of vehicles, but we focus on cars and trucks (which are mostly light trucks, i.e. SUVs, although in some cases could be medium-duty trucks as well), excluding motorcycles, boats, etc. As previously, we classify households into the two skill groups based on the college education of the respondent. Bins of household income before tax are used as an alternative grouping of households.

The data are available since 2006 but we use it for 2009–2015 for consistency with the Ward’s sample.

⁵⁶We have not used any Nielsen or Census data in this section. These products may or may not be in our final sample.

Each household is expected to participate in the survey for four consecutive quarters, so to avoid duplication we only use the most recent survey in which the OVB survey is filled. If the household reports several vehicles in that survey, we use all of them. Like in other datasets we build, we drop vehicles owned by households with income before tax below \$5,000.

Importing data come from Ward’s Automotive Yearbooks. We use the electronic versions of the 2011, 2013, 2014, and 2016 yearbooks. Each of them shows the statistics for the previous two years, thus covering the entire 2009–2015 period. In each year we use five Ward’s tables. Two are on sales in the U.S. (U.S. Car Sales by Line by Month and same for Light Trucks): for each model (also called “lines,” e.g. Chevrolet Camaro) they decompose the number of cars and SUVs sold in the U.S. into those built within and outside NAFTA. The other three tables (U.S. Vehicle Production by Line by Month and same for Mexico and Canada) report production by country and model, allowing us to decompose vehicles assembled within NAFTA into those built in the U.S., Canada, and Mexico.

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

We dropped a small fraction of CEX purchases for brands that we do not observe in Ward’s because their production was discontinued before 2009. Oldsmobile is the most frequent brand we have to drop. All dropped brands combined constitute less than 1.5% of the sample. We also keep four brands (Daewoo, MG, Austin-Healey, Zenn) which are in CEX but not in Ward’s, and are fully imported. This results in the sample of 45 brands listed, with their frequency in the sample, in Table A6.

Linked CEX-Census Dataset. To account for the use of intermediate inputs in the automotive industry, we use the 2012 version the Census of Manufacturers and the Customs data for the same year. We match these data to measures of the consumer base from the CEX. To increase sample size, we use all years of the CEX when the brand variable is available, from 2006 to 2015. In this analysis, we include cars only, not SUVs.

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

Our sample includes two types of observations. If a firm has no production in the U.S., we keep its brands separately and assign 100% imports, both direct and total. And if a firm has some U.S. production (and participated in the 2012 Census of Manufacturers),⁵⁷ we aggregate its brands together and measure

⁵⁷Participation in the quinquennial Census is required by law, so the vast majority of firms reply. However, not all of them

import shares.

The value of imports of assembled cars is defined as total imports in the Customs data in the Harmonized Trade Classification (HS) code 8703 “Motor cars and other motor vehicles principally designed for the transport of persons”.⁵⁸ Imports of car parts are defined as those in HS codes 8706 (chassis fitted with engines), 8707 (bodies for motor vehicles), 8708 (parts and accessories of motor vehicles), 84 (machinery), 85 (electrical machinery and equipment), 90 (measuring and other instruments), 39 (plastics), 40 (rubber), 73 (articles of iron and steel), 83 (miscellaneous articles of base metal), and 94 (furniture).

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

B.5 Combining Estimates on Differential Spending on Imports

Sections 3 and 4–5 estimated the differences in spending on imports across and within industries, respectively. In this section, we combine those estimates using the within-between decomposition (A27). Because our microdata cover only a subset of industries, this requires extrapolation of the patterns within consumer packaged goods and automobiles into other traded industries. We assume that covered industries are representative in terms of the relative difference in import spending.

Formally, we rewrite (A27) in terms of differences as fractions of the average spending on imports:

$$\frac{\Delta_{\text{Final}} [IP_{\mathbf{c}}]}{\mathbb{E}_{\text{Final}} [IP_{\mathbf{c}}]} = \frac{\Delta_{\text{Final}}^{\text{between}} [IP_{\mathbf{c}}]}{\mathbb{E}_{\text{Final}} [IP_{\mathbf{c}}]} + \mathbb{E}_{\text{Imports}} [\omega_g \cdot \text{Rel diff}_{g\mathbf{c}}],$$

where $\mathbb{E}_{\text{Imports}} [\cdot]$ is the average across sectors weighted by spending on imports and $\text{Rel diff}_{g\mathbf{c}} = \frac{\Delta_{\text{Final}} [IP_{\mathbf{c}}|g]}{\mathbb{E}_{\text{Final}} [IP_{\mathbf{c}}|g]}$ is the difference in import spending between the two consumer groups within a group of industries g , as a fraction of the average. The adjustment term is $\omega_g = \frac{\mu_g(1-\mu_g)}{\bar{\mu}(1-\bar{\mu})} \approx 1$.⁵⁹

For imports from all countries, the between-term equals to -4.79%, according to Table 2. Tables 3 and 4 estimate that Rel diff_g is +4.34% in the Nielsen data and +11.34% for automobiles and SUVs, respectively. Averaging those weighted by the total spending on imports in those categories, we get +6.43%.⁶⁰ Therefore, our final estimate of the differential spending on imports is +1.64% of the average.

do, and the information on participation is confidential.

⁵⁸This HS code includes some vehicles besides cars (e.g. SUVs and ambulances), which may create some upward bias.

⁵⁹To prove this representation, we use (A30). Applying the law of total covariance to its numerator, we isolate the within component: $\Delta_{\text{Final}}^{\text{within}} [IP_{\mathbf{c}}] = \mathbb{E}_{\text{Final}} \left[\frac{\text{Cov}[\mu_j, IP_{j\mathbf{c}}|g]}{\bar{\mu}(1-\bar{\mu})} \right] = \mathbb{E}_{\text{Final}} \left[\omega_g \cdot \frac{\text{Cov}[\mu_j, IP_{j\mathbf{c}}|g]}{\mu_g(1-\mu_g)} \right] = \mathbb{E}_{\text{Final}} [\omega_g \cdot \Delta_{\text{Final}} [IP_{\mathbf{c}} | g]] = \mathbb{E}_{\text{Final}} [IP_{\mathbf{c}}] \cdot \mathbb{E}_{\text{Imports}} [\omega_g \cdot \text{Rel diff}_{g\mathbf{c}}]$.

⁶⁰For Nielsen, we only use the within-industry component of the difference to avoid double-counting (see Section 4.2). Moreover, Nielsen data should cover all food and beverages, but its coverage in other industries, e.g. chemicals, is only partial. Therefore, we reduce the weight of all non-food Nielsen categories by a factor of two.

We perform analogous calculations for trade with China, NAFTA, and developed economies specifically and report the results in Table A7. When looking at imports from China, automobiles and SUVs do not play a significant role (China accounted for less than 0.2% of U.S. car imports in 2007, according to the data from Schott (2008)), so we only use the Nielsen data. Similarly, we attribute all car imports from outside NAFTA to developed economies, which indeed accounted for over 99% of total non-NAFTA imports. We use the resulting numbers for calibrations reported in Tables 7 and A13.

B.6 Using QCEW to Impute Skill Intensity

Our goal is to decompose the total payroll in each detailed I-O industry by education group. To do so, we first do it for detailed six-digit NAICS (N6) industry codes and then aggregate up by I-O. We use two pieces of data. First, in QCEW we observe total payroll and the average wage \bar{w}_{N6} for each N6 industry. Second, from IPUMS ACS we know payroll of college- and non-college workers separately, from which we compute skill intensity—the college share of payroll v_{IND} , but it is only available for more aggregated industries, based on the ACS variable IND.⁶¹

In the model, skill intensity of any industry or group of industries j is linearly related to the average wage:

$$\begin{aligned}\bar{w}_j &= w_U (1 - v_j) + w_S v_j, & \text{hence} \\ v_j &= \alpha_0 + \alpha_1 \bar{w}_j,\end{aligned}\tag{A31}$$

where $\alpha_0 = -w_U / (w_S - w_U)$ and $\alpha_1 = 1 / (w_S - w_U)$. Empirically, we recognize that this relationship differs across sectors, so we allow α_0 and α_1 to vary across two-digit NAICS sectors, denoted N2.

Equation (A31) holds in theory both across more aggregate IND industries, where we observe both v_j and \bar{w}_j , and across detailed N6, where we only observe the right-hand side variable. Therefore, we estimate this equation at the IND level (by least squares with payroll weights) and then impute v_{N6} from it. The prediction equals:

$$v_{N6}^{\text{imputed}} = v_{IND} + \alpha_{1,N2} \cdot (\bar{w}_{IND} - \bar{w}_{N2}).$$

We verify that estimates of $\alpha_{1,N2}$ are positive for all sectors and that wages have substantial predictive power: the adjusted R^2 of regression of v_j on N2 fixed effects goes up from 65.1% to 82.8% when wages (with N2-specific coefficient) are included. We constrain the imputed skill intensity to lie between 0 and 1 in rare cases where the prediction is outside this interval.

This imputation preserves the average skill intensity from ACS. This allows us to build a weighted crosswalk to assign for each ACS respondent a set of probabilities that this person works in each N6 and thus I-O industry, based on their IND industry and college dummy. These probabilities differ between college and non-college workers: for example, a N6 industry with low average wages will have lower

⁶¹ We match ACS industries to NAICS using a crosswalk provided by IPUMS (available at <https://usa.ipums.org/usa/volii/indcross03.shtml>). Only in one case (NAICS industry 519130) the same N6 code corresponds to two IND codes. We split this N6 code into two proportionately to the IND payroll.

weight for college graduates. We use this crosswalk to do inference for measures of differential labor market exposure in Section 6.2.

B.7 Census Data for Skill Intensity and Exports

To measure the relationship between skill intensity and exporting at the plant level in Robustness Appendix D.3, we use Census microdata. We focus on the manufacturing sector because it is the only one where the information of the worker types is available and it is the most tradable sector.

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

We use MOPS questions 32–35, which ask for number of managers and employees, as well as the share of managers and non-managers with a college (bachelor) degree.⁶² The shares are listed in terms of discrete bins, so we use the midpoints of those bins.⁶³ This yields an estimate of the share college graduates in total employment, v_j^{Emp} . Unfortunately we do not observe wages of college- and non-college workers. Therefore, to impute the payroll share we use the economy-wide average wages of these groups from the U.S. Census Bureau (DeNavas-Walt et al. 2011). They show that the median wage of college graduates is about 80% higher than that of non-college workers (considering individuals in the labor force and 25 years or older), so we measure the payrolls share of college graduates in each establishment j as

$$v_j = \frac{1.8 \cdot v_j^{\text{Emp}}}{1.8 \cdot v_j^{\text{Emp}} + (1 - v_j^{\text{Emp}})}.$$

It is very strongly correlated with v_j^{Emp} , so the details of imputation are not consequential.

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

⁶²The questionnaire is available at <https://www2.census.gov/programs-surveys/mops/technical-documentation/questionnaires/mop-2010.pdf>; also see Bloom et al. (2016). We drop observations where answers to any of these questions are missing.

⁶³The bins are under 20%, 21–40%, 41–60%, 61–80%, and over 80% for managers and 0%, 1–10%, 11–20%, and over 20% for non-managers (we assign 25% to the last category).

C Econometric Appendix

C.1 Inference for the Expenditure Channel Decomposition

In this section we describe how standard errors can be constructed for the differential shares of import spending if randomness comes from the sampling of firms (as we assume in Section 4), rather than in the sample of consumers in other sections. Suppose there is a set of firms indexed by f . Each of them is characterized by the outcome y_f (the import share) and non-negative spending levels in dollars by the skilled and unskilled people, denoted S_f and U_f , which are positive in expectation.⁶⁴ Our population object of interest is the differential expectation of the outcome in consumption baskets of the skilled and unskilled:⁶⁵

$$\theta = \mathbb{E} \left[\frac{S_f}{\mathbb{E}[S_f]} y_f - \frac{U_f}{\mathbb{E}[U_f]} y_f \right]. \quad (\text{A32})$$

We observe an i.i.d. sample of N firms characterized by (y_f, S_f, U_f) . The plug-in estimator for θ is

$$\hat{\theta} = \frac{\sum_f S_f y_f}{\sum_f S_f} - \frac{\sum_f U_f y_f}{\sum_f U_f}. \quad (\text{A33})$$

We explain how to do inference for $\hat{\theta}$ as well as for the between- and within-group components of it.

Inference on the Weighted Mean. The estimator in (A33) is a difference of two objects. We first show how to do inference on each of them separately, for instance the first one:

$$\hat{\theta}_S = \frac{\sum_f S_f y_f}{\sum_f S_f},$$

which estimates $\theta_S = \mathbb{E}[S_f y_f] / \mathbb{E}[S_f]$. The asymptotic behavior of $\hat{\theta}_S$ follows from Central Limit Theorem and the Slutsky's theorem:

$$\begin{aligned} \sqrt{N} (\hat{\theta}_S - \theta_S) &= \sqrt{N} \left(\frac{\frac{1}{N} \sum_f S_f y_f}{\frac{1}{N} \sum_f S_f} - \theta_S \right) \\ &= \frac{\frac{1}{\sqrt{N}} \sum_f S_f (y_f - \theta_S)}{\frac{1}{N} \sum_f S_f} \\ &\rightarrow \mathcal{N} \left(0, \frac{\text{Var}[S_f (y_f - \theta_S)]}{(\mathbb{E}[S_f])^2} \right). \end{aligned}$$

⁶⁴We will assume that all regularity conditions, such as finiteness of second moments, are satisfied.

⁶⁵To define the estimand with our square-root weighting scheme, we divide S_f and U_f by $\sqrt{S_f + U_f}$, so that they add up to the square root of the actual firm sales. This weighting scheme helps make regularity conditions hold in the data despite the skewed distributions of S_f and U_f .

The variance of $\hat{\theta}_S$ can then be consistently estimated by

$$\begin{aligned}\widehat{Var}(\hat{\theta}_S) &= \frac{1}{N} \frac{\sum_f \left(S_f (y_f - \hat{\theta}_S) \right)^2}{\left(\frac{1}{N} \sum_f S_f \right)^2} \\ &= \frac{\sum_f \left(S_f (y_f - \hat{\theta}_S) \right)^2}{\left(\sum_f S_f \right)^2}.\end{aligned}$$

An analogous expression holds for the estimator $\hat{\theta}_U$ of the weighted mean for the unskilled θ_U .

Inference on Difference in Means. Now come back to the estimator (A33), which satisfies

$$\hat{\theta} - \theta = \frac{\frac{1}{N} \sum_f S_f (y_f - \theta_S)}{\frac{1}{N} \sum_f S_f} - \frac{\frac{1}{N} \sum_f U_f (y_f - \theta_U)}{\frac{1}{N} \sum_f U_f}.$$

Because both denominators converge in probability to a non-zero number and numerators have zero expectations, noise in the estimation of the denominator does not increase the variance. Hence we can write:

$$\begin{aligned}\sqrt{N}(\hat{\theta} - \theta) &= \frac{1}{\sqrt{N}} \sum_f \left\{ \frac{S_f}{\mathbb{E}[S_f]} (y_f - \theta_S) - \frac{U_f}{\mathbb{E}[U_f]} (y_f - \theta_U) \right\} \\ &\rightarrow^p \mathcal{N} \left(0, \text{Var} \left[\frac{S_f}{\mathbb{E}[S_f]} (y_f - \theta_S) - \frac{U_f}{\mathbb{E}[U_f]} (y_f - \theta_U) \right] \right).\end{aligned}$$

The variance of $\hat{\theta}$ can be consistently estimated as

$$\begin{aligned}\widehat{Var}(\hat{\theta}) &= \frac{1}{N^2} \sum_f \left\{ \frac{S_f}{\frac{1}{N} \sum_f S_f} (y_f - \hat{\theta}_S) - \frac{U_f}{\frac{1}{N} \sum_f U_f} (y_f - \hat{\theta}_U) \right\}^2 \\ &= \sum_f \left\{ \frac{S_f}{\sum_f S_f} (y_f - \hat{\theta}_S) - \frac{U_f}{\sum_f U_f} (y_f - \hat{\theta}_U) \right\}^2.\end{aligned}\tag{A34}$$

This formula can be extended to the case of clustering in the standard way.

Regression Representation. While formula (A34) provides the analytical expression for $\widehat{Var}(\hat{\theta})$, a slightly different (in finite samples) but also consistent variance estimator can be obtained using the standard regression toolkit. Note that $\hat{\theta}_S$ is the slope of a simple regression of $y_f \sqrt{S_f}$ on $\sqrt{S_f}$ without a constant, and $\hat{\theta}_U$ can be obtained in an analogous way. Estimating these two regressions simultaneously, e.g. using the `suest` command in Stata, we can get robust or clustered standard errors for $\hat{\theta}_S - \hat{\theta}_U = \hat{\theta}$ without implementing (A34) manually.

Within and Between. Now suppose that firms are classified into groups g , such as industries. We will think of the sample as a sample of groups within which we observe all firms. We also assume that there is a large sample of groups. The objects of interest are the between- and within-group components of $\hat{\theta}$:

$$\hat{\theta}^{\text{between}} = \frac{\sum_g S_g \bar{y}_g}{\sum_g S_g} - \frac{\sum_g U_g \bar{y}_g}{\sum_g U_g},$$

$$\hat{\theta}^{\text{within}} = \frac{\sum_f S_f (y_f - \bar{y}_g)}{\sum_f S_f} - \frac{\sum_f U_f (y_f - \bar{y}_g)}{\sum_f U_f},$$

where $S_g = \sum_{f \in g} S_f$ and $U_g = \sum_{f \in g} U_f$ are the group sizes and $\bar{y}_g = \sum_{f \in g} (S_f + U_f) y_f / (S_g + U_g)$ is the group-level average outcome. One can easily verify that $\hat{\theta} = \hat{\theta}^{\text{between}} + \hat{\theta}^{\text{within}}$.

The between part is just a version of our estimator (A33) defined at the group level. With a large sample of groups, we can directly apply the variance estimator (A34). The within-part is the same as $\hat{\theta}$ with the outcome variable $y_f - \bar{y}_g$. This outcome variable is correlated within the group. Still, a clustered version of (A33) is consistent for the variance of $\hat{\theta}^{\text{within}}$.

In practice we use the regression representation while clustering at the firm-level for the overall effect and clustering at the group level for the within and between components.

C.2 Estimation of Income Elasticities

Here we describe the procedure used to estimate income elasticities for each I-O industry in Section 6, based on the CEX data from Section 3.1. Our approach is inspired by equation (A8), which shows that ψ_j can be estimated directly from the relationship between spending and consumer expenditure, as long as the log-linear approximation works well and different consumers face the same prices. By taking this approach, we avoid estimating the primitive parameters φ_j structurally. Intuitively, higher-income consumers have larger expenditure shares on income-elastic products. Using this logic, we first compute the income *semi*-elasticity for each spending category by regressing spending shares on the logged total expenditure and then convert the estimates to elasticities and aggregate them into the I-O industries.

Specifically, we split households in the CEX sample into 11 bins by the reported pre-tax household income and compute consumption shares across 671 spending categories j for each of the bins i separately (s_j^i) and overall (s_j). Then for each spending category we estimate the income *semi*-elasticity by regressing, across income bins, spending shares on the log of total expenditure in this income group, averaged across households:

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

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

$$\psi_j = 1 + \frac{\hat{\beta}_j}{s_j}.$$

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

$$\sum_j \psi_j s_j = \sum_j s_j + \sum_j \hat{\beta}_j = 1 + 0 = 1,$$

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

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

In unreported results we have verified that our income elasticity estimates are broadly consistent with the estimates from [Aguiar and Bilal \(2015\)](#).

C.3 Bias-Corrected Estimation of Consumption Segmentation

Section [D.2](#) studies the attenuation bias in the estimates of differential import spending in the Nielsen-Census merged data due to the aggregation of import shares at the firm-level. That section links this bias to the ratio of consumption segmentation indices at the level of barcodes and firms. Here we show that naïve estimates of consumption segmentation are not consistent and derive a bias-corrected estimator.

For the population of goods j , which may be individual barcodes or firm-level composites, the consumption segmentation index is defined as

$$\text{Cons}_{\text{segm}} = \frac{\text{Var} [\mu_j^*]}{\bar{\mu}^* (1 - \bar{\mu}^*)},$$

where μ_j^* is the population share of skilled consumers in purchases of good j , with $\bar{\mu}^*$ denoting its mean across all products, and the mean and variance are weighted by some observed measure ω_j of the importance of the good (the square-root of sales with our main weighting scheme). We only observe a random sample of consumers h and their expenditures, from which we estimate the consumer base:

$$\mu_j = \sum_h s_{jh} \text{College}_h,$$

where College_h is an indicator for whether the consumer is a college graduate and s_{jh} is the share of consumer h in the observed sales of good j .

The section argues that the variance of μ_j across goods is an inconsistent, upward biased, estimate of $\text{Var} [\mu_j^*]$ and develops a bias-corrected estimator.⁶⁶ We make two simplifying assumptions. First,

⁶⁶A similar approach to bias correction is found in [Chetty and Hendren \(2017, sec V.A\)](#).

we assume that μ_j is independent across goods, which would be true if the sets of consumers were not overlapping. Second, we treat consumption shares s_{jh} as non-random, only studying sample variation coming from the college dummy. An approach similar to the one in Econometric Appendix C.1 can be potentially developed to take random shares into account.

Since the sample of consumers is i.i.d. for each good, μ_j is unbiased for μ_j^* , and we can write $\mu_j = \mu_j^* + \epsilon_j$ with a mean-zero noise $\epsilon_j = \sum_j s_{jh} (\text{College}_h - \mathbb{E}[\text{College}_h | j])$ that is uncorrelated with μ_j^* . As a result, the weighted variance of observed μ_j across goods includes the fundamental variance of μ_j^* and the average variance of the noise:

$$\text{Var}[\mu_j] = \text{Var}[\mu_j^*] + \mathbb{E}[\sigma_j^2], \quad (\text{A35})$$

where $\sigma_j^2 = \mathbb{E}[\epsilon_j^2]$. If unbiased estimates $\hat{\sigma}_j^2$ are available for σ_j^2 , averaging them across goods yields an unbiased estimate of $\mathbb{E}[\sigma_j^2]$, which is also consistent if the set of goods is growing. Subtracting it from $\widehat{\text{Var}}[\mu_j]$ then yields a bias-correct estimate of $\text{Var}[\mu_j^*]$.

An unbiased estimator for σ_j^2 can be obtained by noticing that ϵ_j is just a weighted average of a random sample, hence

$$\sigma_j^2 = HHI_j \cdot \text{Var}[\text{College}_h | j], \quad (\text{A36})$$

where $HHI_j = \sum_h s_{jh}^2$ is the Herfindahl index that measures the (inverse) effective number of consumers of this good. Here $\text{Var}[\text{College}_h | j]$ depends on the good—for example, a good which fundamentally sells 99% to college graduates will have very little sample variation in μ_j . This fundamental variance can be estimated as a transformation of the sample variance of College_h among observed consumers. Indeed,

$$\begin{aligned} \mathbb{E} \left[\sum_h s_{jh} \left(\text{College}_h - \sum_{h'} s_{jh'} \text{College}_{h'} \right)^2 \right] &= \left(\sum_h s_{jh} (1 - s_{jh})^2 + \sum_h s_{jh} \sum_{h' \neq h} s_{jh'}^2 \right) \cdot \text{Var}[\text{College}_h | j] \\ &= (1 - HHI_j) \cdot \text{Var}[\text{College}_h | j]. \end{aligned}$$

Since we treat weights, and therefore HHI_j , as non-random, $\sum_h s_{jh} (\text{College}_h - \mu_j)^2 / (1 - HHI_j)$ is unbiased for $\text{Var}[\text{College}_h | j]$. Plugging this into (A36), we get

$$\hat{\sigma}_j^2 = HHI_j \cdot \frac{\sum_h s_{jh} (\text{College}_h - \mu_j)^2}{1 - HHI_j}.$$

With equal weights, $\hat{\sigma}_j^2$ becomes a familiar unbiased variance estimator with $N - 1$ in the denominator. Plugging it into (A35), we obtain a consistent estimator of $\text{Var}[\mu_j^*]$:

$$\widehat{\text{Var}}[\mu_j^*] = \sum_j \omega_j (\mu_j - \bar{\mu})^2 - \sum_j \omega_j \hat{\sigma}_j^2.$$

Dividing through by $\bar{\mu}(1 - \bar{\mu})$ transforms it into the consumption segmentation index.

D Additional Results and Robustness

D.1 The Segregation Channel

Any increase in the college wage premium will have a negative impact on consumers who purchase goods that are produced using skilled labor, because production cost went up. If college graduates tend to buy goods from industries or firms that employ relatively more college graduates, then an increase in the college wage premium (e.g., caused by trade) has a direct benefit for college graduates through the earnings channel, but it also has an indirect cost through the (relative) increase in their price index. We refer to this indirect channel as the “segregation” channel. For a formal expression of the segregation channel, see equation (8) in the main text (without input-output linkages) and equation (A18) in the online Appendix (accounting for input-output linkages). This section reports the differences in skill intensity of consumption baskets across consumer types, which govern the segregation channel. We do so first at the industry level and then within consumer packaged goods.

Industry-Level Results. Panel (a) of Figure A6 documents segregation patterns at the industry level. The binned scatter plot shows that there is no strong relationship between the share of industry sales to college graduates and its share of payroll to college graduates. The payroll share is adjusted for input-output linkages, i.e., reflects the entire supply chain of domestic production in the industry. We find that the slope is positive but small, reflecting a very small and statistically insignificant difference in the average college payroll share between the college and non-college consumption baskets: 46.2% vs. 46.0%, with a difference of 0.19pp. Because the change in the college wage premium induced by trade shocks we considered in Section 7 is always smaller than the average gain, and it gets multiplied by 0.19%, the implied price effects are very small. Therefore, the segregation channel does not meaningfully affect the distributional effects of trade at the industry level.

The segregation channel could potentially operate in other contexts where shocks cause a larger change in the skill premium (e.g., automation), which could be a fruitful avenue for future research. For recent and related work on the segregation channel, see [Wilmers \(2017\)](#) and [Clemens et al. \(2018\)](#).

Results for Consumer-Packaged Goods. Panel (b) of Figure A6 reports the segregation results within consumer packaged goods, at the level of firms. The binned scatter plot shows an increasing relationship between the share of firm payroll to non-production workers (as a proxy for the skilled group within the Census) and the fraction of sales to college graduates. Although the relationship appears robust graphically and is highly statistically significant, the magnitude remains relatively small. Given differences in spending patterns within consumer packaged goods, this pattern implies that the payroll share of skilled workers is 1.18 percentage points larger for college-educated consumers. Although larger than in the industry-level analysis, this difference is still not strong enough for the segregation channel to generate substantial distributional effects from trade for the same reason as above (i.e., it gets multiplied by the relatively small response of the college wage premium to trade shocks)

D.2 Differences in Spending on Imports of Consumer Packaged Goods

In this section we check robustness of the results to different weights and discuss some concerns with the estimation, stemming from underestimating of retailer imports and measuring imports at the firm rather than barcode level.

Weighting Schemes. All results in the main text are based on the square-root weighting scheme, which reduces the influence of a small number of giant firms for which our proxy for the import share is noisier. In unreported results we verify that all findings are very similar, both qualitatively and quantitatively, when firms are weighted by their Nielsen sales to the power of $1/4$ or $3/4$ instead of $1/2$, as well as by square-root of the firm’s sales in the Census.

Table A19 presents the estimates of the differential import spending using full Nielsen sales weights. Within-industry differences follow the same pattern as with square-root weights in Tables 3 and A5: imports from China are anti-skilled while imports from other countries are pro-skilled, and the latter dominates in the total. However, the magnitudes of within-industry differences are even weaker than before: they are under 6% of the average pro-skilled for all cases excluding China and under 2.5% anti-skilled for China. Also, across-industry differences play a much bigger role.

Final and Intermediate Products. Table A20 attempts to isolate direct and indirect imports, i.e. imports of final goods and intermediate inputs. We do not classify *products* into final and intermediate. Instead we consider the main activity of the firm that registered the barcode. We find that imports by wholesalers explain most of the difference in import spending across education groups, and these are likely imports of final products.⁶⁷ Specifically, imports by wholesalers capture the entire pro-skilled effect for total imports (columns (1)–(3)) and over 60% of the anti-skilled effect for Chinese imports in health and household products (columns (4)–(6); this is the product class for which this effect is significant in Table A5).

Import Shares for Retailers. We measure the import share for a barcode as the fraction of imports in sales of the firm that registered it. This proxy underestimates the total share of imports in the firm’s sales if the domestic firm is buying imported products through domestic intermediaries. In the industry-level data from Section 3, such higher-order indirect spending contributes only 2.7 p.p. to the total spending on imports of 12.6% reported in Table 2 (and of the 5.7% of indirect spending). However, it is likely to be much more important in the retail sector, where firms obtain products from wholesalers, including foreign products. As a consequence, retailers in our Nielsen sample (with square-root weights) have a low average import share of 2.2%, compared with 7.4% for manufacturers and 16.5% for wholesalers (Table A21).

⁶⁷Imports by manufacturers can be imports of intermediates or, if the firm is engaged in multinational products, imports of final products as well. We do not have to take a stand on this because imports by manufacturing firms do not generate substantial difference in import spending, as reported in the table.

It is important to highlight that this underestimated import share applies only for barcodes that are *registered* by retailers—think of a subset of Walmart own brands rather than everything Walmart sells (see Data Appendix B.3). Although most of Nielsen sales happen *through* retailers, they involve products registered by other firms, for which we have independent measures of import shares. Only 18.6% of total Nielsen sales is in products registered by retailers (8.7% with square-root weights).

Still, retailer brands target less skilled clients, with the average share of college graduates of 28.6% for retail relative to 28.9% for manufacturers and 29.7% for wholesalers (Table A21). Therefore, adding missing imports by retailers could potentially create an anti-skilled pattern of trade. However, columns (3) and (6) of Table A20 suggest that such bias is unlikely to be important. The differential spending that is generated by retailers is under -0.02 p.p., both for total imports and for imports from China. Even if imports by retailers were underestimated by a factor of ten, this would not make any significant difference.

Attenuation Bias from Aggregation within Firms. One limitation of our data is that imports are measured at the firm level. Although the analysis is much more detailed than any industry-level study (recall that we have 12,700 firm-year observations for only 71 I-O industries), the import proxy is aggregated across barcodes sold by each firm. Here we show that under plausible assumptions, our estimates of the differential import spending may be attenuated but at most by a factor of 1.5.

To build intuition, note that aggregation of barcodes can generate bias only if two conditions are satisfied. First, different barcodes of the same firm are sold to sufficiently different groups of consumers. If all barcodes have the same consumer mix, it does not matter which particular one is imported and which is domestic. Second, import shares should be systematically related to the consumer mix within a firm.

The degree of within-firm heterogeneity in consumer mix is observable, as the Nielsen data provide us with measures of consumer mix for each barcode. We estimate that about 2/3 of the variation in consumer across barcodes, as measured by the consumption segmentation index, is across firms. Moreover, we assume that the relationship between import shares and consumer mix (i) has the same sign between and within firms and (ii) cannot be stronger within, as firms tend to have coherent sourcing strategies that apply to many of their products. These conditions imply that our estimates are attenuated and put an upper bound on the degree of attenuation.

Formal Analysis. We exploit two decompositions from Theory Appendix A.5. We first decompose the true difference in import spending at the level of barcodes j into the sum of components across firms f (which we showed to be pro-skilled in the main analysis) and within firms (which is unobserved):

$$\Delta_{\text{Final}} [IP_j] = \Delta_{\text{Final}}^{\text{between}} [IP_f] + \Delta_{\text{Final}}^{\text{within}} [IP_j]. \quad (\text{A37})$$

The between component is positive, as firms selling to more educated consumers import more. Formalizing this equivalence, (A28) implies

$$\Delta_{\text{Final}}^{\text{between}} [IP_j] = \beta^{\text{between}} \cdot \text{Segm}_{\text{cons}}^{\text{firm}},$$

where β^{between} is the slope of the firm-level regression of IP_f on μ_f and $\text{Segm}_{\text{cons}}^{\text{firm}}$ is the firm-level consumption segmentation index. The within component permits a similar representation:

$$\Delta_{\text{Final}}^{\text{within}} [IP_j] = \bar{\beta}^{\text{within}} \cdot \text{Segm}_{\text{cons}}^{\text{within}},$$

where $\bar{\beta}^{\text{within}} = \frac{\mathbb{E}[\beta_f \cdot \text{Var}[\mu_j|f]]}{\mathbb{E}[\text{Var}[\mu_j|f]]}$ is a weighted average of firm-specific slopes β_f in regressions of IP_j on μ_j , and $\text{Segm}_{\text{cons}}^{\text{within}} = \text{Segm}_{\text{cons}}^{\text{barcode}} - \text{Segm}_{\text{cons}}^{\text{firm}}$ (the proof is directly obtained by applying the law of total covariance to equation (A30)).

Now assume that $\bar{\beta}^{\text{within}}$ is between zero and β^{between} . For example, if $\beta^{\text{between}} > 0$, we assume $0 < \bar{\beta}^{\text{within}} < \beta^{\text{between}}$. Then from (A37), $\Delta_{\text{Final}} [IP_j]$ is bounded by $\Delta_{\text{Final}}^{\text{between}} [IP_j]$ and

$$\beta^{\text{between}} \cdot \text{Segm}_{\text{cons}} = \Delta_{\text{Final}}^{\text{between}} [IP_j] \cdot \underbrace{\frac{\text{Segm}_{\text{cons}}}{\text{Segm}_{\text{cons}}^{\text{firm}}}}_{\text{Attenuation ratio}},$$

where the attenuation ratio is always above or equal to 1.

Estimation. If we could observe consumer base of each barcode perfectly, computing the attenuation ratio would be a trivial exercise. Unfortunately, for many barcodes the fraction of college-graduated consumers has to be estimated from a small sample of consumers, which leads to an excess variance and upward biased consumption segmentation, particularly at the barcode level, where the sample size is smaller. However, we address this issue in Econometric Appendix C.3, deriving an unbiased and consistent estimate of segmentation.

Table A22 estimates segmentation at the barcode and firm-module levels for all products and for each of the three product classes separately. Without the bias correction, it appears that segmentation is more than twice as high at the barcode level, which would allow for stronger attenuation of the differential import spending. However, almost half of the barcode-level segmentation turns out to be noise, and the ratio of bias-corrected segmentation indices is only 1.42. It is slightly larger for health & household (1.61) and even more so in general merchandize (2.17), which may partially explain why Table A5 found smaller differential import spending patterns in those parts of the product space.

Multiplying the estimates from Table 3 by these ratios, we get the upper bound on differential import spending at the barcode level under our assumptions. The maximum anti-skilled effect is for China in health & household products, and it is bounded by 8.7% of the average. At the same time, the pro-skilled differential spending on imports excluding China in food may potentially be as large as 22.8% of the average.

D.3 Differences in Labor Market Exposure to Trade

Import Penetration and Skill Intensity over Time. The positive relationship between skill intensity and import penetration within the goods-producing sector appears to be a relatively recent phenomenon. To show this, Figure A7 groups manufacturing industries into bins by their skill intensity in 1992, 1999, and 2007 (Panels (a)–(c), respectively) and reports the average import penetration for each bin in the corresponding year. Because we do not have the I-O tables for years other than 2007, we use a combination of the NBER CES dataset to measure domestic output and the Schott (2008) imports data, in both cases for 6-digit manufacturing NAICS industries.⁶⁸ Skill intensity in the NBER CES is measured as the payroll share of non-production workers.

The figure shows that the relationship between import penetration and skill intensity was flat in 1992, weakly increasing in 1999, and became quite steep in 2007: moving from the 25th percentile of skill intensity to the 75th percentile, the import penetration grows by 6.6 p.p., or 38% of its mean.

Skill Bias of Exporters within Industries. It is well-known that in the cross-section exporting firms, which are more productive than non-exporters, tend to also have higher skill intensity (for U.S. evidence, see for example Bernard et al. 2007). However, we show that pattern is mostly captured by industries, and within industries export shares are at most very weakly correlated with skill intensity.

Columns (3)–(4) or Table 6 capture the across-industry component of this skill bias of exports. Burstein and Vogel (2017) find in a multi-country Bernard et al. (2003) type setting that the within-industry skill bias of productivity and exports is sufficient to generate a sizable pro-rich earnings channel. However, reduced-form evidence in the U.S. is mixed. Bernard et al. (2007) find in the 2002 Census of Manufactures that exporting establishments have 19% higher skill intensity relative to the non-exporting ones, and 11% of it survives when industry fixed effects are included. In contrast, the estimates for 2007 from Bernard et al. (2018) suggest a 6% difference, out of which only a statistically insignificant 1% is within industries. Skill intensity is measured in both cases as the employment share of non-production workers.

We confirm the findings of Bernard et al. (2018) in a way consistent with Table 6, measuring the average export share for establishments employing skilled and unskilled people and comparing the two. We estimate the payroll of college-educated and other workers for over 33,000 manufacturing establishments in the 2010 Management and Organizational Practices Survey, which is a supplement to the Annual Survey of Manufactures (MOPS, see Bloom et al. 2016). We also check robustness to using the payroll of non-production and production workers in the full 2007 Census of Manufactures (same data as in Bernard et al. 2018), 2010 Annual Survey of Manufactures which covers larger firms, and its MOPS subsample. Data Appendix B.7 describes data construction.

Table A10 presents the results. In all cases exporters are more skill-intensive than non-exporters but

⁶⁸Import penetration is measured slightly differently than before as the ratio of imports to imports plus domestic output. We do not subtract exports because, due to imperfect concordance from the HS codes, absorption becomes negative in some industries. We verify that the pattern we find holds in the SIC-level data from Autor et al. (2013).

the difference is mostly across industries, so it was already captured in Table 6. The fraction of the within-industry component of the difference varies across specifications from 0.2% to 17.1%. The largest number corresponds to the MOPS case where skill is defined by college education, but is still relatively small.

Skill-Biased Import Competition. Theory Appendix A.3 derives a simple adjustment to the differential exposure to import competition, which is sufficient to capture the case where the marginal set of workers displaced by import competition is representative of the industry skill mix in the past. We implement this adjustment using the 2000 and 1990 IPUMS data from the population censuses, constructing the samples in the same way as in Section 6. Table A23 present the results. As a benchmark, Columns (1) and (2) use the 2007 skill intensity, so the results are unchanged relative to the case with just one segment per industry, as in Table 6. College workers have lower exposure to imports but the difference is only 3.2% of the average without the I-O adjustment, or 9.4% with it. Columns (3) and (4) use the 2000 data, where college graduates accounted for 46.1% of the total labor income, compared to 49.7% in 2007. Correspondingly, the difference in exposure to import competition grows substantially, to 24.3% of the average without the I-O adjustment and 19.3% with it. The pattern becomes even larger when using the data from 1990 in columns (5)–(6), with the average skill intensity of only 41.4%. The differential exposure equals 58.9% (35.6%) of the average without (with) the I-O adjustment, which predicts that the earnings channel may be more pro-skilled than in our baseline estimates.

To check the quantitative importance of these patterns, we reestimated the counterfactual effects of a 10% bilateral trade liberalization with all trading partners, as in Section 7, accounting for the skill-bias of importing. We found a moderate change in how pro-skilled the earnings channel is: it increases from 20.6% of the average gains to 29.2% using the 2000 skill intensity and to 44.0% using the data from 1990.

D.4 The Earnings Channel for Capital Owners vs. Workers

Table A11 investigates whether workers and capital owners are differentially exposed to the earnings effects of trade. This table follows the same logic as Table 6 in the main text, except that it compares workers and capital owners instead of workers with and without a college degree. The methodology is the same, except that we now use Gross Operating Surplus from the I-O table as factor income of capital owners (replaced with zero in a small number of industries where it is negative), and we use total payroll in QCEW for workers.

Table A11 shows that the earnings effects of trade are relatively similar for workers and capital owners. Columns (1) and (2) show the average exposure to import penetration. Without I-O linkages, capital owners are 1.51pp more exposed to import penetration; this difference slightly increases to 1.68pp (18.2% of average exposure) when I-O linkages are accounted for. Exposure to exports is virtually identical for capital owners and workers with and without I-O linkages (Columns (3) and (4)). Exposure to imported inputs is also similar across the two groups (Columns (5) and (6)). Finally, Columns (7) and (8) show that capital owners specialize in industries that have a smaller income elasticity. Average income elasticity with

factor income weights is about 11.5pp smaller for capital owners (accounting for I-O linkages). Therefore capital owners should benefit less from the income effects resulting from the average gains from trade. The following rows of Table A11 document that this difference primarily results from differences within goods and within services, and more specifically between the subsectors. Nonetheless, the earnings effects from differential income elasticities are likely to be relatively small (see Section 7).

The reduced-form pattern thus indicate that workers and capital owners are similarly exposed to the earnings effects of trade. Similar results hold when considering exposure to trade with China specifically (not reported).

D.5 Calibrations for Observed Changes in Trade Costs

While Section 7 analyzed hypothetical trade shocks that are uniform across industries, here we consider the distributional effects of other counterfactuals based on shocks observed in the data. We calibrate the effects of three shocks: the removal of Trump tariffs (on solar panels, washing machines, steel and aluminum products, and Chinese products), the observed change in tariffs between 1992 and 2007, and the observed change in “import charges” (defined as transportation and insurance costs) in the same period.

Methodology and Data. The formulas in our model section capture the effects of a shock to importing trade costs of the same magnitude $\hat{\tau}$ for all imports from a set of countries \mathbf{c} . A slight modification is necessary to capture a shock that varies across industries in proportion to some variable r_j , i.e., $\hat{\tau}_j = r_j \hat{\tau}$. Indeed, in this case the industry import price index equals $(IP_{j\mathbf{c}} r_j / IP_j) \cdot \hat{\tau}$ instead of $(IP_{j\mathbf{c}} / IP_j) \cdot \hat{\tau}$. Thus, simply replacing $IP_{j\mathbf{c}}$ with $IP_{j\mathbf{c}} r_j$ allows us to estimate the counterfactual changes of the equilibrium in the first order approximation. We describe below how \mathbf{c} and r_j are defined for each of the three shocks we consider. In all three cases, we first measure the shock at the level of HS codes and then average it at the level of the corresponding I-O code using the HS-NAICS concordance from Schott (2008) and Pierce and Schott (2012).

The first shock is the set of tariffs introduced by the Trump administration in 2018. For consistency with other analyses, we model the removal of these tariffs rather than their introduction, so that the implied average gains are positive. We combine three sets of tariffs:

1. *Solar panels and washing machines.* Actual tariffs on solar panels and large residential washing machines have a complicated structure: their rates vary over time, they are combined with quotas, and certain exceptions are provided, as described in Presidential Proclamations 9693 and 9694 of January 23, 2018. We approximate these rates by using the base rates (30% for solar panels and 20% for washers) applied to the main HS codes described in the Proclamations and to all U.S. trading partners.
2. *Steel and aluminum products.* Tariff duties on imports of steel and aluminum by trading partners are given in Section 232 of the Trade Expansion Act of 1962. The tariff increases were proposed on

March 1 and amended on May 31, 2018. We identify the steel and aluminum products that were affected by these tariffs increases using the published lists of HS codes. We apply a 25% tariff on steel products, excluding imports from Argentina, Australia, Brazil and South Korea, and a 10% tariff on aluminum products excluding Argentina and Australia.

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

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

Results. The results are reported in Table A12. Column (1) shows the welfare impact of the removal of Trump tariffs.⁶⁹ Expressed as a percentage of initial consumption spending, the average welfare gain is 0.051%; it is larger for college graduates (0.075%) than for households without a college degree (0.028%). The expenditure channel is close to perfectly neutral and the difference between households with and without a college degree comes entirely from the earnings channel. Unreported analyses indicate that this difference primarily results from the fact that the metal industry is very low skill intensive and highly protected by the Trump tariffs (their removal would therefore hurt low-skill workers).

Column (2) reports the results for the observed change in tariff duties between 1992 and 2007. Tariffs and duties have fallen during this period by 1.65pp on average (using 2007 import weights), inducing an average welfare gain of 0.15% of initial consumption, which is quite similar for households with and without a college degree (with welfare gains of 0.163% and 0.136%, respectively). The expenditure channel induces virtually no difference between education groups, while the earnings channel slightly favors college graduates.

Finally, Column (3) shows the welfare effects of observed changes in transportation and insurance costs between 1992 and 2007. The trend of falling import charges during this period (by 0.95pp on average) led to an average welfare gain of 0.136% of initial consumption, which is again quite similar across education groups, ranging from 0.126% for college graduates to 0.141% for households without a college degree. The earnings channel is very slightly in favor of college graduates. In this counterfactual,

⁶⁹Note that we apply these tariffs to the equilibrium observed in 2007, as in the main analysis. We obtain similar results when updating the data to 2015; some of these results are reported in a recent New York Times article (Bui and Irwin 2018).

the expenditure channel is no longer perfectly neutral: it contributes to larger welfare gains for households without a college degree, although the difference remains modest, equal to 15% of the average welfare gain. In unreported analyses, we find that the expenditure channel favors low-skill households because they spend relatively more on product categories like gas and food, for which the fall in import charges was particularly pronounced.

References

- Aguiar, Mark, and Mark Bils.** 2015. “Has Consumption Inequality Mirrored Income Inequality?” *American Economic Review* 105:2725–2756.
- Antràs, Pol, Davin Chor, Thibault Fally, and Russell Hillberry.** 2012. “Measuring the Upstreamness of Production and Trade Flows Three Measures of Upstreamness.” *American Economic Review: Papers & Proceedings* 102:412–416.
- Autor, David H., David Dorn, and Gordon H. Hanson.** 2013. “The China Syndrome: Local Labor Market Impacts of Import Competition in the United States.” *American Economic Review* 103:2121–2168.
- Autor, David H., Lawrence F Katz, and AB Krueger.** 1998. “Computing inequality: have computers changed the labor market?” *The Quarterly Journal of Economics*: 1169–1213.
- Berman, Eli, John Bound, and Zvi Griliches.** 1994. “Changes in the Demand for Skilled Labor Within U. S. Manufacturing: Evidence From the Annual Survey of Manufactures.” *The Quarterly Journal of Economics* 109:367–397.
- Berman, Eli, John Bound, and Stephen Machin.** 1998. “Implications of skill-biased technological change: international evidence.” *The Quarterly Journal of Economics* 113:1245–1279.
- Bernard, Andrew B., Jonathan Eaton, J. Bradford Jensen, and Samuel Kortum.** 2003. “Plants and Productivity in International Trade.” *American Economic Review* 93:1268–1290.
- Bernard, Andrew B., J. Bradford Jensen, Stephen J. Redding, and Peter K. Schott.** 2007. “Firms in international trade.” *Journal of Economic Perspectives* 21:105–130.
- . 2018. “Global Firms.” *Journal of Economic Literature* 56:565–619.
- Bernard, Andrew B., J. Bradford Jensen, and Peter K. Schott.** 2006. “Survival of the best fit: Exposure to low-wage countries and the (uneven) growth of U.S. manufacturing plants.” *Journal of International Economics* 68:219–237.
- . 2009. “Importers, Exporters and Multinationals: A Portrait of Firms in the U.S. that Trade Goods.” In *Producer Dynamics: New Evidence from Micro Data*, 513–552.
- Bloom, Nicholas, Erik Brynjolfsson, Lucia Foster, and Ron Jarmin.** 2016. “What Drives Differences in Management?”
- Borjas, George J., Richard B. Freeman, and Lawrence F. Katz.** 1997. “How Much Do Immigration and Trade Affect Labor Market Outcomes?” *Brookings Papers on Economic Activity*.

- Buera, Francisco J, Joseph P Kaboski, and Richard Rogerson.** 2015. “Skill Biased Structural Change.” *NBER Working Paper*.
- Bui, Quoc Trung, and Neil Irwin.** 2018. “How Much Will the Trade War Cost a Typical American Family? Around \$60 (So Far).” *New York Times*.
- Burstein, Ariel, and Jonathan Vogel.** 2017. “International Trade, Technology, and the Skill Premium.” *Journal of Political Economy* 125:1356–1412.
- Caliendo, Lorenzo, and Fernando Parro.** 2015. “Estimates of the trade and welfare effects of NAFTA.” *Review of Economic Studies* 82:1–44.
- Chetty, Raj, and Nathaniel Hendren.** 2017. “The Impacts of Neighborhoods on Intergenerational Mobility II: County-Level Estimates.”
- Clemens, Jeffrey, Joshua D Gottlieb, Morten Olsen, and H David.** 2018. “The Spillover Effects of Top Income Inequality.”
- Comin, Diego, Danial Lashkari, and Martí Mestieri.** 2016. “Structural Change with Long-run Income and Price Effects.” *Working Paper*.
- Cravino, Javier, and Sebastian Sotelo.** 2018. “Trade Induced Structural Change and the Skill Premium.” *Working Paper*.
- DeNavas-Walt, Carmen, Bernadette D. Proctor, and Jessica C. Smith.** 2011. “Income, Poverty, and Health Insurance Coverage in the United States: 2010.” *U.S. Census Bureau Current Population Reports* (Washington, D.C.).
- DeSalvo, Bethany, Frank F. Limehouse, and Shawn D. Klimek.** 2016. “Documenting the Business Register and Related Economic Business Data.”
- Duncan, Otis Dudley, and Beverly Duncan.** 1955. “Residential Distribution and Occupational Stratification.” *American Journal of Sociology* 60:493–503.
- Galle, Simon, Andrés Rodríguez-clare, and Moises Yi.** 2017. “Slicing the Pie: Quantifying the Aggregate and Distributional Effects of Trade.” *Working Paper*.
- Hanoch, Giora.** 1975. “Production and Demand Models with Direct or Indirect Implicit Additivity.” *Econometrica* 43:395–419.
- Horowitz, Karen J., and Mark A. Planting.** 2009. *Concepts and Methods of the U.S. Input-Output Accounts*. Washington, D.C.: Bureau of Economic Analysis, Department of Commerce.
- Jaimovich, Nir, Sergio Rebelo, and Arlene Wong.** 2015. “Trading Down and the Business Cycle.” *NBER Working Papers* September.
- Kamal, Fariha, and Ryan Monarch.** 2016. “Identifying Foreign Suppliers in U.S. Merchandise Import Transactions.” *CES working paper*.
- Lee, Eunhee.** 2016. “Trade, Inequality, and the Endogenous Sorting of Heterogeneous Workers.” *Working paper*.
- Levinson, Arik, and James O’Brien.** 2017. “Environmental Engel Curves.” *Working Paper*.
- Oberfield, Ezra, and Devesh Raval.** 2014. “Micro Data and Macro Technology.” *Working Paper*.

- Pierce, Justin R., and Peter K. Schott.** 2012. “A Concordance Between Ten-Digit U.S. Harmonized System Codes and SIC/NAICS Product Classes and Industries.” *Journal of Economic and Social Measurement* 37:61–96.
- Schott, Peter K.** 2008. “The relative sophistication of Chinese exports.” *Economic Policy* 23:6–49.
- Timmer, Marcel P., Erik Dietzenbacher, Bart Los, Robert Stehrer, and Gaaitzen J. de Vries.** 2015. “An Illustrated User Guide to the World Input-Output Database: the Case of Global Automotive Production.” *Review of International Economics* 23:575–605.
- Tintelnot, Felix, Ayumu Ken Kikkawa, Magne Mogstad, and Emmanuel Dhyne.** 2017. “Trade and Domestic Production Networks.”
- Wasi, Nada, and Aaron Flaaen.** 2015. “The Stata Journal.” *Stata Journal* 15:672–697.
- Wilmers, Nathan.** 2017. “Does Consumer Demand Reproduce Inequality ? High-income Consumers, Vertical Differentiation and the Wage Structure.” *American Journal of Sociology* 123:178–231.

Additional Tables and Figures

Table A1: Notation for Model without Input-Output Linkages

Indices	$i \in \{S, U\}$	Group of agents: S (skilled) or U (unskilled)
	j, r	Industry; Sector (goods or services)
	c	Country: H (Home), F (Foreign), \mathbf{c} (affected by import shock)
Prices, Quantities, Transaction Values	p_{jc}	Consumer price of country- c variety in industry j
	p_j	Consumer price index in industry j
	Q_{jc}^i, X_{jc}^i	Quantity and expenditure of group i on variety jc
	Q_j^i, X_j^i	Composite quantity and expenditure of group i in industry j
	$Q_{jH}, Q_{jH}^{\text{Export}}$	Domestic output and exports in j (quantity)
	X_j	Total domestic expenditure on industry j
	X_i	Total domestic expenditure by group i
	X_{jH}, VA_j	Total value of output and value added by domestic industry
Wages, Employment	w_i, \bar{w}	Wage for group i , average wage
	L_i, L_i^j	Measure of group i consumers; industry employment
Equilibrium Shares	$s_j^i, s_j^{\text{Final}}$	Share on industry j in expenditure of group i , both groups
	e_i^j	Share of industry j in group i earnings and employment
	$\mu_j, \bar{\mu}$	Share of skilled consumers in final sales, by industry and overall
	v_j, \bar{v}	Share of skilled workers in payroll, by industry and overall
	$IP_{jc}, IP_{j\mathbf{c}}, IP_j$	Import penetration: share of country c , set of countries \mathbf{c} , or all foreign countries in domestic expenditure in industry j
Counterfactual Changes	Hats	Relative change from original to counterfactual equilibrium
	$\hat{\tau}$	Counterfactual growth of import barriers (with countries \mathbf{c})
	$\hat{\tau}^*$	Counterfactual growth of export barriers (with all partners)
	\hat{U}_i	Money metric of welfare growth
	$\hat{\pi}_i, \hat{\pi}$	Laspeyres price index for group i and both groups together
Elasticities	$\xi_j, \varepsilon_r, \rho$	Substitution between country varieties in j ; between industries within sector r ; between goods and services
	ψ_j	Income elasticity in j
	$\sigma_j, \sigma_{\text{macro}}$	Elasticity of substitution between labor types in domestic production in j and at macro level
	η_j^{import}	Negative elasticity of industry VA w.r.t. import tariff
	η_j^{export}	Elasticity of industry VA w.r.t. export tariff
	$\eta_j^{\text{avg wage}}$	Elasticity of industry VA w.r.t. domestic average wage
	Averages and Differences Across Industries	$\mathbb{E}_{\text{Final}}[\cdot]$
	$\Delta_{\text{Final}}[\cdot]$	Difference between averages weighted by s_j^S and s_j^U
	$\mathbb{E}_{\text{VA}}[\cdot]$	Average weighted by domestic value added
	$\Delta_{\text{VA}}[\cdot]$	Difference between averages weighted by e_S^j and e_U^j

Notes: This table lists the notation for the model in Section 2. “With respect to” is abbreviated to “w.r.t.”

Table A2: Classification of Subsectors

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

* Subsectors with zero final personal consumption (either in the input-output table or in the CEX, or both).

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

Table A3: Differences in Import Spending by Consumer Education: The Role of Goods and Services

	Share of Services in Total Spending	Share of Imports in Spending by Sector			
		From All Countries		From China	
	(1)	Goods (2)	Services (3)	Goods (4)	Services (5)
All consumers, %	67.71	28.80	4.85	5.21	0.37
College consumers, %	70.28	29.67	4.84	5.87	0.38
Non-college consumers, %	66.01	28.30	4.86	4.84	0.36
College minus non-college, p.p.	+4.27	+1.37	-0.02	+1.03	+0.02

Notes: This table provides evidence on the role of goods and services in explaining the differences in spending shares on imports between consumer education groups. Using industry-level data from Section 3, it shows that services constitute a large share of spending for college graduates (column (1)) and have lower import content (including imported intermediate inputs and measured as % of absorption). Yet, within goods the share of spending on imports is larger for college graduates (columns (2)–(5)).

Table A4: Summary Statistics, Merged Nielsen-Census Sample

	All Products	By Product Class		
		Food	Health & Household	General Merchandise
Total Imports (% of Firm Sales)	11.10	6.92	14.58	27.96
Imports from China	4.15	0.88	6.51	17.91
Imports from NAFTA	1.91	1.67	2.19	2.74
Imports from Developed Economies	3.10	2.42	4.24	4.90
% of Firm-Module Sales to College Graduates (st.dev.)	31.18 (12.62)	31.34 (13.54)	30.71 (11.05)	31.12 (9.44)
% of Product Class in Total Sales	100.00	67.29	20.24	12.48
<i>N</i> firms	8,200	5,700	2,400	2,000
<i>N</i> firm-years	12,700	9,000	3,700	2,800
<i>N</i> firm-module-years	131,000	88,600	29,800	12,500

Notes: This table reports statistics on imports based on the merged Nielsen-Census sample from Section 4, for all products and for three product classes: Food, Alcohol, and Tobacco (“Food”), Health and Beauty Products and Household Supplies (“Health and household”), and General Merchandise. Imports are measured at the firm level and the summary statistics are computed using the square-root of firms’ Nielsen sales as weights. The reported percentage of each product class uses the same weighting scheme. When computing the percentage of firm-module sales to college graduates, weights are decomposed across barcodes of the same firm proportionally to sales. Observations are firm-module-year cells and the numbers of observations are rounded to the nearest 100 to preserve confidentiality.

Table A5: Spending on Imports by Education Group and Product Class,
Merged Nielsen-Census Sample

	Imports Excluding China by Product Class			Imports from China by Product Class		
	Food	Health & Household	General Merchandise	Food	Health & Household	General Merchandise
	(1)	(2)	(3)	(4)	(5)	(6)
All, %	6.04	8.07	10.04	0.88	6.51	17.91
College, %	6.75	8.16	10.41	0.85	6.27	17.65
Non-college, %	5.72	8.03	9.88	0.90	6.62	18.03
College minus non-college, p.p.	+1.03	+0.13	+0.54	-0.04	-0.35	-0.38
	(0.12)	(0.17)	(0.22)	(0.03)	(0.14)	(0.28)
<i>as % of avg. import spending</i>	<i>17.06</i>	<i>1.61</i>	<i>5.37</i>	<i>-4.98</i>	<i>-5.38</i>	<i>-2.13</i>
→ Within industries	+0.73	+0.21	+0.36	+0.01	-0.33	-0.30
	(0.113)	(0.11)	(0.17)	(0.023)	(0.18)	(0.13)
<i>as % of avg. import spending</i>	<i>12.14</i>	<i>2.55</i>	<i>3.62</i>	<i>0.57</i>	<i>-5.12</i>	<i>-1.67</i>
→ Within product modules	+0.498	+0.13	+0.39	-0.00	-0.43	-0.32
	(0.080)	(0.09)	(0.15)	(0.015)	(0.08)	(0.18)
<i>as % of avg. import spending</i>	<i>8.25</i>	<i>1.56</i>	<i>3.88</i>	<i>-0.11</i>	<i>-6.59</i>	<i>-1.76</i>
<i>N firm-years</i>	9,000	3,700	2,800	9,000	3,700	2,800

Notes: This table reports the fraction of imports in expenditure for different education groups using the merged Nielsen-Census sample from Section 4. Importing is proxied by the share of total imports in firm sales. Differential spending on imports is decomposed into “within” and “between” components for 6-digit I-O codes (“industries”) and for Nielsen product modules (“product modules”) according to equation (A27). The same firm may operate in more than one product class. Firms are weighted by the square-root of Nielsen sales. Standard errors are shown in parentheses.

Table A6: List of Motor Vehicle Brands

Brand Code	Brand	<i>N</i>	Brand Code	Brand	<i>N</i>	Brand Code	Brand	<i>N</i>
FOR	Ford	15,592	KIA	KIA	1,554	ISU	Isuzu	250
CHE	Chevrolet	14,608	LEX	Lexus	1,398	SAA	Saab	198
TOY	Toyota	12,002	MEC	Mercury	1,376	POR	Porsche	181
HON	Honda	8,740	BMW	BMW	1,257	MIN	Mini	176
DOD	Dodge	6,427	SAT	Saturn	1,244	LAN	Land Rover	145
NIS	Nissan	5,478	MRB	Mercedes-Benz	1,170	JAG	Jaguar	140
JEE	Jeep	3,179	ACU	Acura	1,146	ZEN	Zenn	96
GMC	GMC	2,782	CAD	Cadillac	1,130	HUM	Hummer	72
CHR	Chrysler	2,495	MIT	Mitsubishi	935	DAW	Daewoo	34
PON	Pontiac	2,330	LIN	Lincoln	800	FIA	Fiat	25
HYU	Hyundai	2,317	VOV	Volvo	710	SMA	Smart	21
BUI	Buick	2,268	INF	Infiniti	568	MGA	MG	16
MAZ	Mazda	1,867	AUD	Audi	446	TES	Tesla	11
VOK	Volkswagen	1,737	SUZ	Suzuki	348	INT	Intl. Harvester	10
SUB	Subaru	1,680	SCI	Scion	315	AUS	Austin-Healey	4

Notes: This table lists 45 brands in the sample on motor vehicles (cars and SUVs), described in Section 5.1 and reports the total number of purchases in the CEX sample.

Table A7: Combining Microdata and Industry-Level Data for Expenditure Channel

Imports from	Difference in import spending, college minus non-college, % of average							
	Consumer packaged goods	Cars	→	Within industries, weighted average	+	Between industries	=	Total
	(1)	(2)		(3)		(4)		(5)
All countries	4.34	11.43		6.43		-4.79		1.64
China	-2.44	—		-2.44		6.57		4.13
NAFTA	3.20	-16.60		-2.66		-9.07		-11.73
Developed economies	12.27	50.64		23.61		-7.94		15.67

Notes: This table estimates the total difference in import spending between college and non-college consumers (as % of the average) by combining the industry-level estimates from Section 3 with microdata evidence from Sections 4 and 5, according to the methodology described in Data Appendix B.5. Figures in Column (1), (2), and (4) replicate those from Tables 3 (row “Within industries”), 4, and 2, respectively. Column (3) is a weighted average of columns (1) and (2), with weights corresponding to the total spending on imports covered by the Nielsen and vehicle microdata, and column (5) is the total of columns (3) and (4).

Table A8: Differences in Import Penetration by Worker Education: the Role of Goods and Services

	Share of Services	Import Penetration by Sector	
	in Total Payroll	Goods	Services
	(1)	(2)	(3)
All workers, %	85.32	23.85	0.55
College workers, %	88.68	28.06	0.82
Non-college workers, %	81.99	21.23	0.26
College minus non-college, p.p.	+6.69	+6.84	+0.57

Notes: This table provides evidence on the role of goods and services in explaining the differential exposure to import competition between worker education groups. Using industry-level data from Section 6, it shows that services constitute a larger share of payroll for college graduates (column (1)) and have lower import penetration (direct imports as % of absorption). Yet, within goods and within services, the exposure to import competition, measured as the average import penetration weighted by group-specific payroll shares, is larger for college graduates (columns (2)–(3)).

Table A9: Exposure to Import Competition by Worker Education and Trading Partner, Industry Data

	Payroll-weighted Import Penetration by Trading Partner (even columns adjust for input-output linkages)					
	China		NAFTA		Developed Economies	
	(1)	(2)	(3)	(4)	(5)	(6)
All workers, %	0.65	1.22	0.85	1.92	1.41	2.94
College-educated workers, %	0.59	1.10	0.69	1.65	1.37	2.80
Non-college educated workers, %	0.71	1.33	1.00	2.20	1.45	3.08
College minus non-college, p.p.	-0.13	-0.23	-0.31	-0.55	-0.08	-0.28
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
<i>as % of avg.</i>	-19.47	-18.71	-37.02	-28.58	-5.74	-9.39
→ Between goods and services	-0.30	-0.35	-0.38	-0.50	-0.64	-0.79
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
→ Within goods and services	+0.17	+0.13	+0.07	-0.05	+0.56	+0.52
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
→ Between subsectors	+0.17	+0.16	+0.08	-0.01	+0.41	+0.40
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
→ Within subsectors	-0.00	-0.03	-0.00	-0.04	+0.14	+0.12
	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)

Notes: This table reports average import penetration statistics weighted by total payroll and payroll of college- and non-college educated workers separately, using the industry-level data from Section 6, which covers 380 industries. It also decomposes the difference between education groups into the within and between components for sectors (goods and services) and subsectors (listed in Table A2), according to equation (A27). Import penetration is measured as imports from a given set of countries as % of industry absorption. Even columns account for import penetration in downstream industries (see Section 2.3 for details).

Table A10: Skill-Bias of Exporters in Census Microdata

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

Notes: This table shows the average export shares (exports as % of sales) for three samples of manufacturing establishments: the 2010 MOPS (columns (1) and (4)), the 2007 Census of Manufactures (column (2)) and the 2010 Annual Survey of Manufactures (column (3)). It also shows the differential exposure for skilled and unskilled workers and decomposes it into “between” and “within” components across six-digit industries, according to equation (A27). Skilled workers are defined as college graduates in column (1) and non-production workers in the other columns. Establishments are weighted by their total payroll. See Section D.3 for details of data construction.

Table A11: Exposure to Earnings Effects of Trade for Capital Owners and Workers, Industry Data

	Averages with Factor Income Weight							
	Import Penetration		Export Share		Imported Inputs Share		Income Elasticity $\times 100$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
All, %	4.70	9.26	4.81	9.48	6.66	13.46	103.89	101.58
Capital owners, %	5.48	10.13	4.94	9.57	6.79	14.01	97.47	95.66
Workers, %	3.97	8.44	4.68	9.39	6.54	12.95	109.92	107.15
Capital owners minus workers, p.p.	1.51	1.68	0.26	0.18	0.25	1.06	-12.45	-11.48
<i>as % of avg.</i>	<i>32.13</i>	<i>18.17</i>	<i>5.35</i>	<i>1.92</i>	<i>3.71</i>	<i>7.88</i>	<i>-11.98</i>	<i>-11.31</i>
→ Between goods and services	1.55	2.02	0.81	1.09	0.79	1.34	-0.88	-0.74
→ Within goods and services	-0.04	-0.34	-0.55	-0.91	-0.54	-0.28	-11.57	-10.74
→ Between subsectors	-0.19	-0.33	-0.44	-0.60	-0.40	0.08	-11.72	-10.19
→ Within subsectors	0.15	-0.01	-0.11	-0.31	-0.15	-0.36	0.15	-0.55
Adjusted for I-O linkages	No	Yes	No	Yes	No	Yes	No	Yes

Notes: This table reports the averages of several industry characteristics, overall and for workers and capital owners separately, using the industry-level data from Section 6. The income of capital owners is measured as the Gross Operating Surplus in the I-O table (replacing negative values with zero for three industries), and the payroll of workers is from QCEW. The table also decomposes the difference into the within and between components for sectors (goods and services) and subsectors (listed in Table A2), according to equation (A27). The outcomes are imports as % of absorption, exports as % of industry output, imports of intermediate inputs as % of output, and income elasticities. Even columns account for imports, exports, imported inputs, and income elasticities in downstream industries.

Table A12: Counterfactual Welfare Effects of Observed Changes in Trade Costs

	Removing Trump	Observed change, 1992-2007	
	import tariffs (1)	Duties (2)	Import Charges (3)
<i>Average welfare effects, equivalent variation as % of spending</i>			
All	0.051	0.150	0.136
College	0.075	0.163	0.126
Non-College	0.028	0.136	0.141
<i>Distributional effects, college minus non-college, p.p. [as % of avg. welfare effect]</i>			
Overall	+0.047 [91.9%]	+0.027 [17.7%]	-0.015 [-10.9%]
→ Expenditure channel, pro-skilled	-0.001 [-2.6%]	-0.004 [-3.0%]	-0.020 [-15.0%]
→ Earnings channel, pro-skilled	+0.048 [94.5%]	+0.031 [20.6%]	+0.006 [+4.1%]

Notes: This table calibrates the welfare effects across education groups for three counterfactual scenarios based on the observed changes in trade costs, as described in Robustness Appendix D.5. These calibrations use the model from Section 2 and the industry-level data from Sections 3 and 6. It reports the welfare effects in terms of equivalent variation, expressed as a percentage of initial consumption spending for each education group. The distributional effects are decomposed into the expenditure channel and the earnings channel according to equation (3).

Table A13: Counterfactual Welfare Effects of Trade Liberalizations with NAFTA and Developed Economies

	10% Reduction in Trade Barriers with	
	NAFTA (1)	34 Developed Economies (2)
<i>Average welfare effects, equivalent variation as % of spending</i>		
All	0.210	0.227
College	0.235	0.288
Non-College	0.179	0.176
<i>Distributional effects, college minus non-college, p.p. [as % of avg. welfare effect]</i>		
Overall	+0.056 [26.6%]	+0.112 [49.3%]
→ Expenditure channel, pro-skilled	-0.032 [-15.3%]	+0.049 [21.4%]
→ Earnings channel, pro-skilled	+0.088 [41.9%]	+0.063 [27.8%]

Notes: This table calibrates the welfare effects of two trade liberalizations (uniform reductions of importing barriers with NAFTA countries and with 34 developed economies) across education groups using the model from Section 2 and the reduced-form patterns from Sections 3–6. It reports the welfare effects in terms of equivalent variation, expressed as a percentage of initial consumption spending for each education group. The distributional effects are decomposed into the expenditure channel and the earnings channel according to equation (3).

Table A14: Nielsen-Census Matching Rules

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

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

Table A15: Nielsen-Census Match Statistics

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

(b) Census Firms in Food, Alcohol, and Tobacco			
	All years		
	Firms	% of Sales	
All Census	51,500	100.00	
Matched to Nielsen	8,900	78.96	
Matched to Nielsen with size filter	5,200	75.57	
Passed Consistency Filter	4,800	58.73	

Notes: This table reports the number of firms and the percentage of total sales remaining after each step of the merging process between the Nielsen and Census samples, explained in detail in Data Appendix [B.3](#). Panel (a) measures these statistics relative to the full Nielsen sample (for 2007 and 2012 Economic Censuses separately), while Panel (b) measures them relatively to the set of Census firms active in the Food, Alcohol, and Tobacco Manufacturing industries (NAICS codes 311 and 312). The last line of each panel corresponds to the final merged sample, for all firms in Panel (a) and for those in food, alcohol, and tobacco in Panel (b). The numbers of firms are rounded to the nearest 100 to preserve confidentiality.

Table A16: Distribution of Match Types, Merged Nielsen-Census Sample

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

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

Table A17: Distribution of NAICS Industries, Merged Nielsen-Census Sample

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

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

Table A18: Nielsen-Census Sample Selection

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

(b) Census Firms in Food, Alcohol, and Tobacco						
	N	% of Sales	Median Sales, \$k	Median Payroll, \$k	Median Employment	Mean Skill Intensity
Matched	4,800	58.73	13,303	1,889	54	0.336
Didn't Match	46,600	41.27	606	113	4	0.341
P-value of t-test						[0.744]

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

Table A19: Spending on Imports by Education Group,
Merged Nielsen-Census Sample, Full Weights

	All products			Food	Health & Household		General Merchandize	
	All	China	Excl. China	Excl. China	China	Excl. China	China	Excl. China
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
All, %	8.16	2.25	5.91	4.50	2.69	8.55	17.17	12.36
College, %	8.58	2.34	6.24	4.83	2.65	8.56	16.81	12.57
Non-college, %	7.99	2.21	5.78	4.37	2.70	8.54	17.34	12.26
College minus non-college, p.p.	+0.59	+0.13	+0.46	+0.46	-0.05	+0.02	-0.53	+0.31
	(0.15)	(0.06)	(0.13)	(0.13)	(0.05)	(0.25)	(0.43)	(0.28)
<i>as % of avg. import spending</i>	<i>+7.20</i>	<i>+5.60</i>	<i>+7.81</i>	<i>+10.16</i>	<i>-1.97</i>	<i>+0.25</i>	<i>-3.10</i>	<i>+2.53</i>
→ Within industries	+0.18	-0.02	+0.20	+0.26	-0.07	+0.04	-0.28	+0.07
	(0.07)	(0.03)	(0.06)	(0.05)	(0.05)	(0.18)	(0.27)	(0.21)
<i>as % of avg. import spending</i>	<i>+2.14</i>	<i>-1.02</i>	<i>+3.35</i>	<i>+5.82</i>	<i>-2.46</i>	<i>+0.41</i>	<i>-1.64</i>	<i>+0.57</i>
N firm-years	12,700	12,700	12,700	9,000	3,700	3,700	2,800	2,800

Notes: This table is analogous to Tables 3 and A5, except using Nielsen sales instead of the square-root of sales as weights. It reports the fraction of imports in expenditure for different education groups using the merged Nielsen-Census sample from Section 4. Column (1) measures all imports; columns (2)–(3) decompose imports into those from China and other countries (“Excluding China”), and the following columns report import shares separately by product class. Imports of food from China are small and not shown. Standard errors are shown in parentheses.

Table A20: Consumer Spending on Imports by Firm Activity: Manufacturing, Wholesale, and Retail (Merged Nielsen-Census Sample)

	Total imports, All products			Imports from China, Health & Household		
	MFG (1)	WH (2)	RT (3)	MFG (4)	WH (5)	RT (6)
All, %	4.37	5.82	0.30	1.98	3.99	0.28
College minus non-college, p.p.	-0.09 (0.07)	0.62 (0.10)	-0.01 (0.02)	-0.11 (0.08)	-0.21 (0.11)	-0.01 (0.02)
→ Within industries	-0.05 (0.05)	0.47 (0.11)	-0.00 (0.01)	-0.10 (0.04)	-0.19 (0.16)	-0.01 (0.02)
<i>N</i> firm-years	12,700	12,700	12,700	3,700	3,700	3,700

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

Table A21: Summary Statistics by Firm Activity, Merged Nielsen-Census Sample

	Firm Activity			
	MFG	WH	RT	Other
Total Imports, % of Firms' Sales	7.37	16.46	2.23	14.98
Imports from China, % of Firms' Sales	1.38	5.67	1.34	6.33
% of Firm-Module Sales to College Graduates	28.98	29.67	28.55	32.35
% of Firm Group in Total Sales	61.63	16.02	18.55	3.80
% of Firm Group in Total $\sqrt{\text{Sales}}$	57.17	29.00	8.66	5.18
<i>N</i> firm-years	6,300	5,000	600	800

Notes: This table reports statistics on imports and consumer education by the main activity of the firm in the merged Nielsen-Census sample: manufacturing (MFG), wholesale (WH), retail (RT), and Other. Each firm is assigned the main activity based on the total payroll of establishments in the corresponding NAICS sectors. Summary statistics are computed using the square-root of firms' Nielsen sales as weights. Numbers of observations are rounded to the nearest 100 to preserve confidentiality.

Table A22: Bias Correction for the Consumption Segmentation Index, Merged Nielsen-Census Sample

	All products (1)	Food (2)	Health & Household (3)	General Merchandise (4)
<i>Naïve estimates of consumption segmentation index, %</i>				
Across barcodes	15.03	15.09	14.10	16.13
Across firm-modules	7.42	8.52	5.74	4.16
<i>Bias-corrected estimates, %</i>				
Across barcodes	8.22	9.21	6.58	5.46
Across firm-modules	5.77	6.87	4.09	2.52
Attenuation ratio	1.424	1.339	1.610	2.165

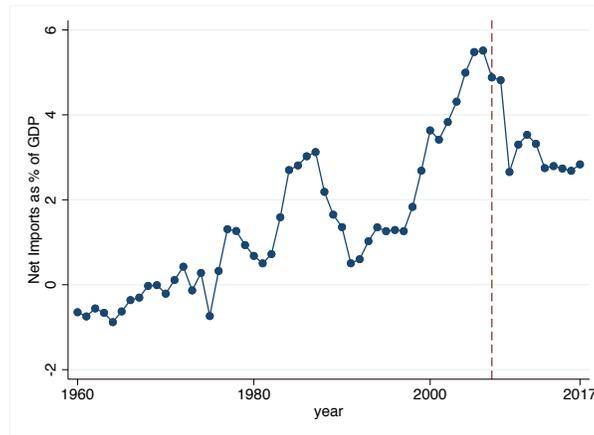
Notes: This table estimates the consumption segmentation index defined by (A28), first using a naïve plug-in estimator and then with the bias-correction procedure developed in Econometric Appendix C.3. The ratio of bias-corrected estimates of segmentation across barcodes and firm-modules, presented in the last row, bounds the attenuation bias in the differential import spending, as explained in Robustness Appendix D.2. Square-root weighting scheme is used throughout. The uncorrected consumption segmentation index for firm-modules is different from the one reported in Section 4.2 because this table does not subtract the within-industry component.

Table A23: Differential Exposure to Skill-Biased Import Competition

	Marginal Displaced Worker is Representative of Skill Intensity in					
	2007		2000		1990	
	(1)	(2)	(3)	(4)	(5)	(6)
All workers, %	3.97	8.44	3.97	8.44	3.97	8.44
College-educated workers, %	3.91	8.05	3.48	7.62	2.79	6.93
Non-college educated workers, %	4.03	8.84	4.45	9.26	5.13	9.94
College minus non-college, p.p.	-0.13	-0.79	-0.96	-1.63	-2.34	-3.01
<i>as % of avg.</i>	<i>-3.21</i>	<i>-9.40</i>	<i>-24.29</i>	<i>-19.31</i>	<i>-58.92</i>	<i>-35.59</i>
Average College Payroll Share	49.70		46.09		41.43	
Adjusted for I-O linkages	No	Yes	No	Yes	No	Yes

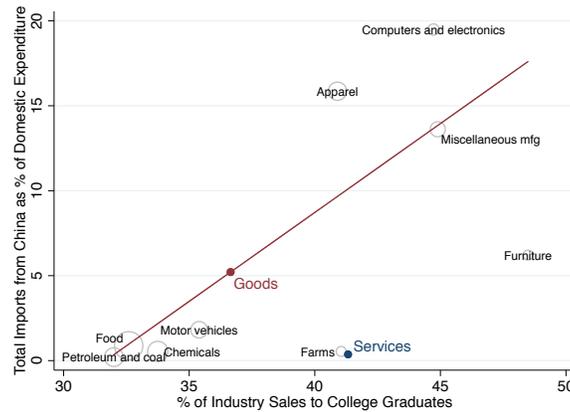
Notes: This table reports the payroll-weighted exposure to import competition by education group assuming that import competition happens in segments of each industry that have the skill mix as in the U.S. in the past. Columns (1) and (2) repeat the results from Table 6 without the skill bias of importing. Columns (3)–(4) use the skill intensity from 2000 as a proxy for the mix of marginally affected workers, and columns (5)–(6) use year 1990. Columns (2), (4), and (6) adjust for input-output linkages. The methodology is described in Robustness Appendix D.3.

Figure A1: U.S. Net Imports as % of GDP over Time



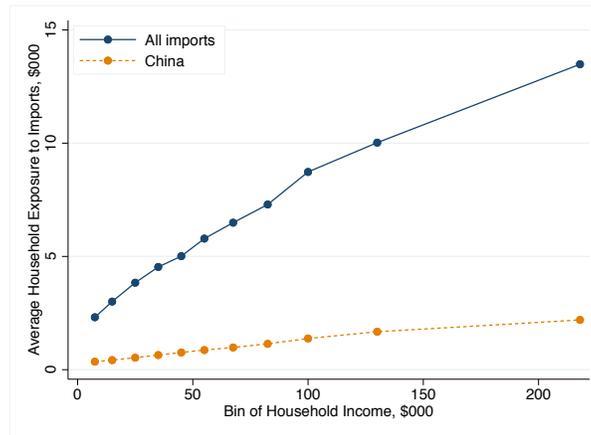
Notes: This figure shows the evolution of the ratio of net imports to GDP in the U.S., using the trade totals published by the Census Bureau (<https://www.census.gov/foreign-trade/statistics/historical/gands.xls>) and GDP statistics from the BEA (<https://www.bea.gov/data/gdp/gross-domestic-product>) for 1960–2017. The vertical line corresponds to the main year of our analysis, 2007.

Figure A2: Imports from China and Consumer Base across Subsectors



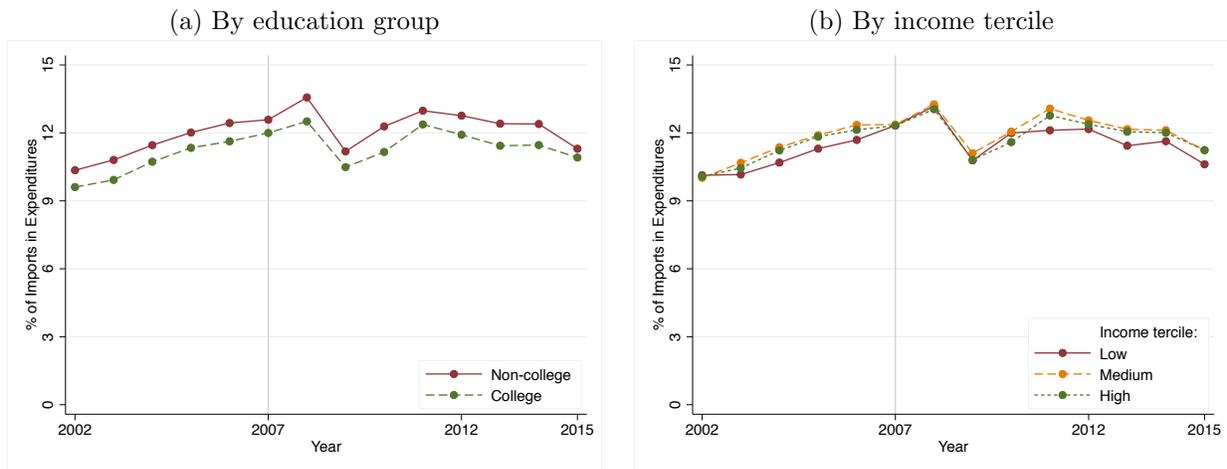
Notes: This figure shows the relationship between consumer base (% of industry sales to college graduates) and the share of total (direct plus indirect) imports from China in final expenditure using industry-level data from Section 3. Each circle corresponds to a subsector within the goods-producing sector (listed in Table A2), and the circle size indicates final spending. Subsectors that take up less than 3% of the sectoral spending are not shown. Only the composite of the service sector is shown because direct imports of services from China are zero in our data by construction and indirect import penetration is very small.

Figure A3: Average Import Expenditure in \$1,000 by Income Groups



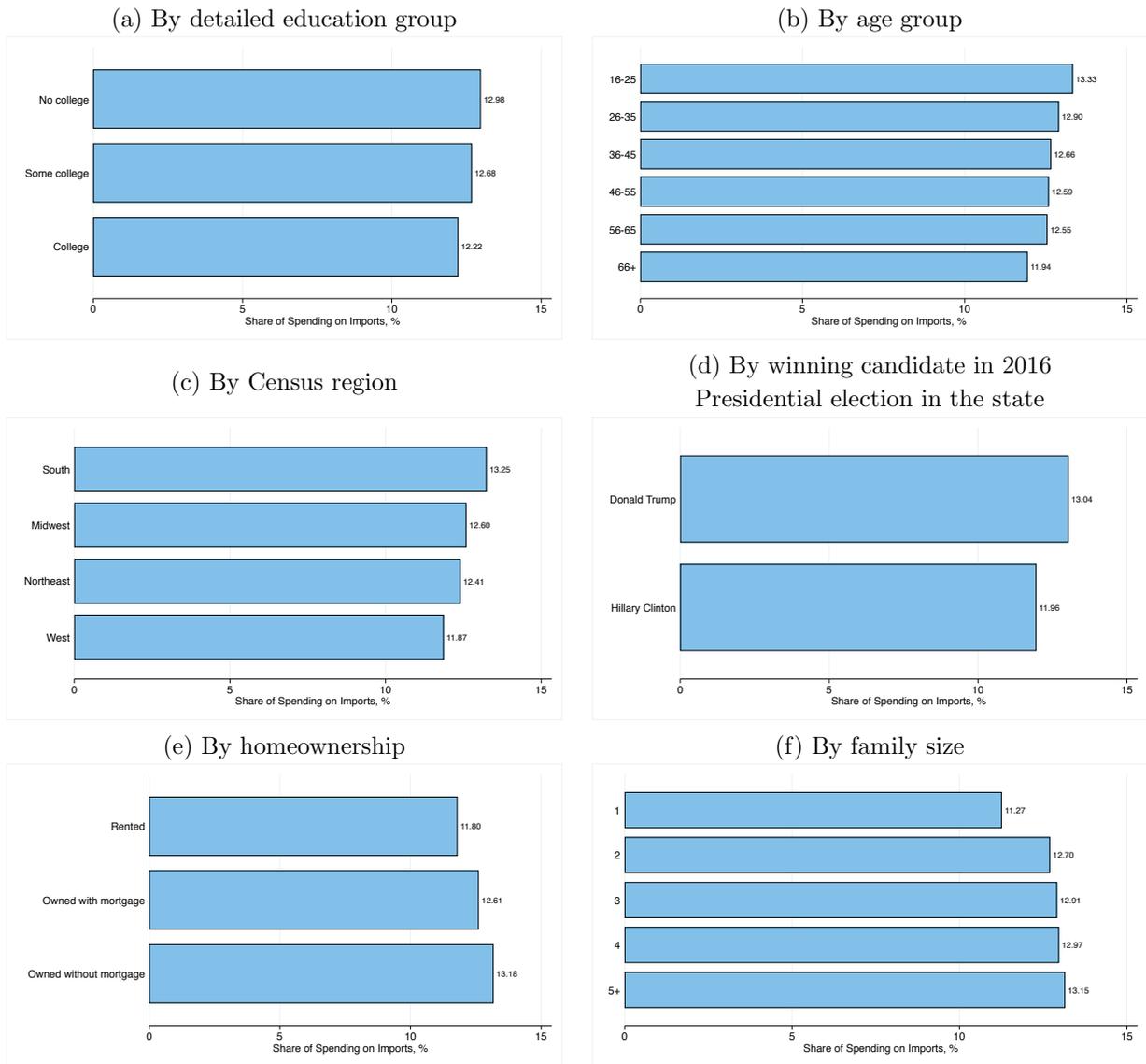
Notes: These binned scatterplots group CEX panelists into 11 bins by household income before tax. They report the average value of total (direct and indirect) imports in the spending of each bin, in \$1,000, computed using the industry-level data from Section 3. The correspond to the shares reported in Figure 2, rescaled by the average of total expenditures among households within each group (computed for the Interview and Diary surveys separately and added up).

Figure A4: Import Share of Expenditures over Time



Notes: This figure shows the total fraction of imports in expenditures by demographic group (college education in Panel (a) and year-specific terciles of income before tax in Panel (b)) for 2002–2015. For each year, it combines the CEX Integrated Survey with the BEA Summary I-O Tables after redefinitions. The methodology is analogous to that of Section 3, except that I-O industries are more aggregated. We use 73 three-digit commodities from the I-O table and separate Non-comparable Imports from the Rest-of-the-World Adjustment. We drop used goods, rest-of-the-world adjustment, and government industries for the final calculation, which results in 71 industry, including 54 final industries matched to the CEX.

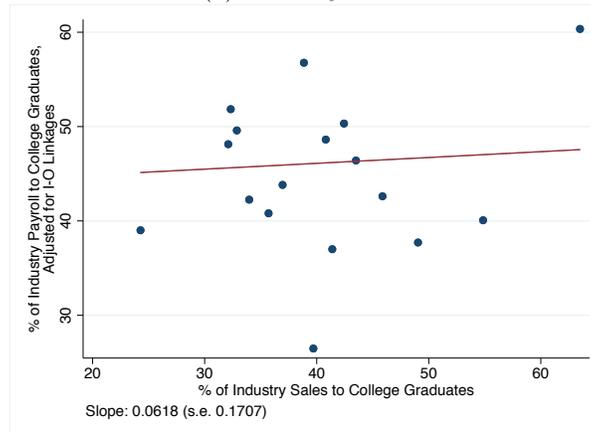
Figure A5: Spending Shares on Imports across Household Groups



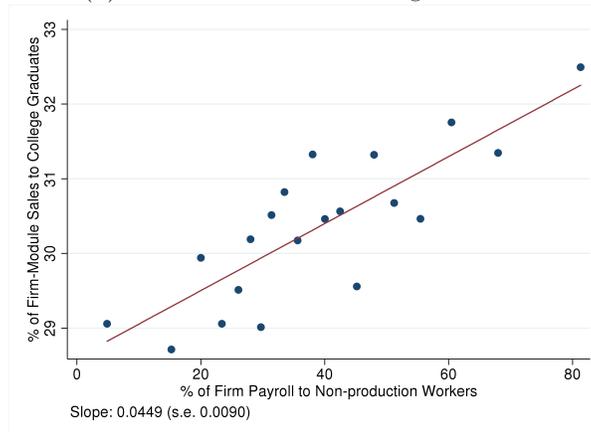
Notes: This figure shows fraction of spending on imports across groups of households, using industry-level data from Section 3. Indirect spending on imports via imported intermediate inputs is taken into account.

Figure A6: The Segregation Channel

(a) Industry-Level

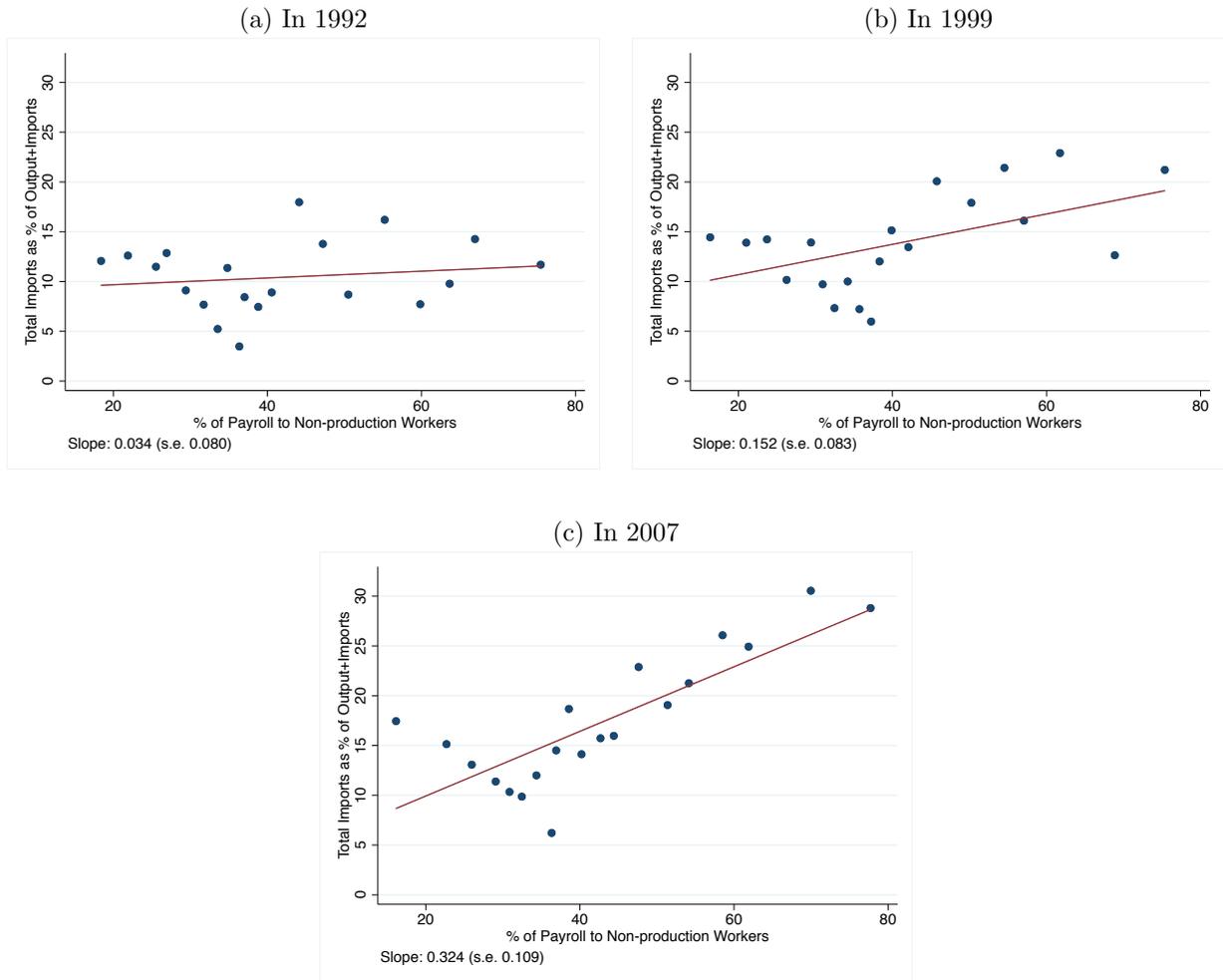


(b) Within Consumer Packaged Goods



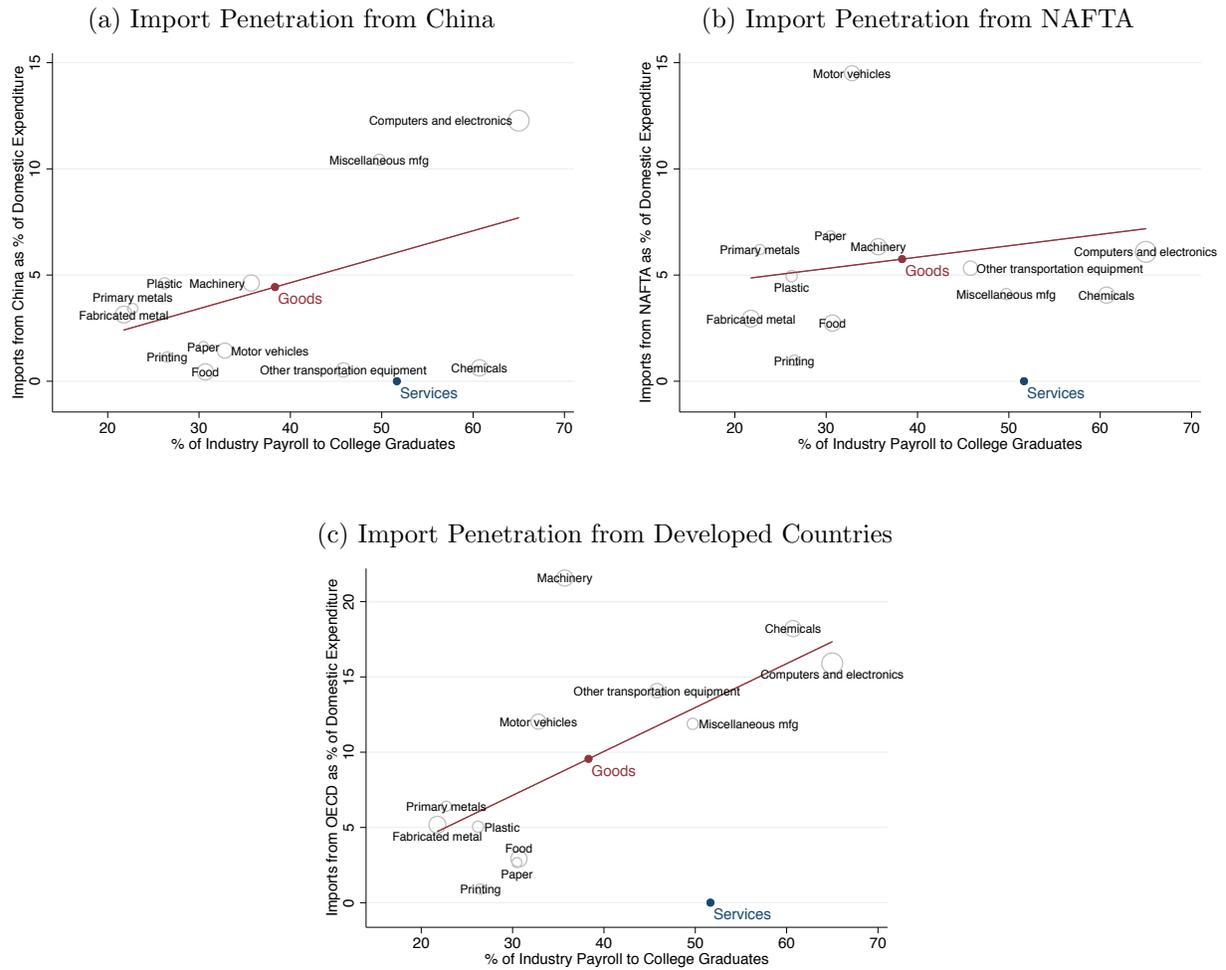
Notes: This figure studies the relationship between industry skill intensity and its fraction of sales to college graduates. Panel (a) of this Figure uses industry level data on spending patterns (from Section 3) and earnings (from Section 6). Skill intensity is adjusted for I-O linkages according to the model in Theory Appendix A.2. Each dot represents 5% of the data, with personal consumption spending weight from the I-O table. Panel (b) reports analogous pattern using the merged Nielsen-Census dataset from Section 4. Firms are weighted by the square-root of their Nielsen sales (weights are split across barcodes of the same firm proportionally to sales) and each dot accounts for 5% of the data.

Figure A7: Import Penetration and Skill Intensity over Time



Notes: These binned scatterplots group 6-digit manufacturing NAICS industries into bins by the measure of skill intensity available in the NBER CES dataset (payroll share of *non-production* workers). It reports import penetration measured as total imports divided by the sum of imports and domestic output. Industries are weighted by payroll ($N = 462$ in 1992 and 465 in the 1999 and 2007). Payroll and skill intensity are from the NBER CES database, and imports at the NAICS level are from [Schott \(2008\)](#) and [Pierce and Schott \(2012\)](#). Several industries in the NBER CES have been aggregated to match those in the Pierce-Schott data (see Robustness Appendix [D.3](#) for details of data construction).

Figure A8: Import Penetration by Country and Skill Intensity



Notes: This figure shows the relationship between skill intensity (payroll share of college graduates) and import penetration from a given set of countries (the share of direct imports in absorption) using industry-level data from Section 6. Each circle corresponds to a subsector within the goods-producing sector (listed in Table A2), and the circle size indicates total payroll. Subsectors that account for less than 3% of the sectoral payroll are not shown. Only the composite of the service sector is shown because direct imports of services from China are zero in our data by construction.

Figure A9: Examples of Products

Domestic Products

(a) Plates “Corelle”

(b) Plates “MainStays”



UPC 071160 015449
World Kitchen, LLC

UPC 018643 157371
Merrick Engineering, Inc.

Imported Products

(c) Bed Sheets “MainStays”,
Made in China

(d) Plates “Better Homes”,
Made in China

(e) Conditioner “Equate Beauty”,
Made in Canada



UPC 844178 030335
Jiangsu Royal Home USA, Inc.

UPC 855602006 567
First Design Global, Inc.

UPC 681131 124836
Wal-Mart Stores, Inc.

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