

# Gains from Trade: Does Sectoral Heterogeneity Matter?

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January 4, 2021<sup>§</sup>

First version: March 2018

**Abstract:** This paper assesses the quantitative importance of including sectoral heterogeneity in computing the gains from trade. Our framework draws from Caliendo and Parro (2015) and has sectoral heterogeneity along five dimensions, including the elasticity of trade to trade costs. We estimate the sectoral trade elasticity with the Simonovska and Waugh (2014) simulated method of moments estimator and micro price data. Our estimates range from 2.97 to 8.94 across sectors. Our benchmark model is calibrated to 21 OECD countries and 20 sectors. We remove one or two sources of sectoral heterogeneity at a time, and compare the gains from trade to the benchmark model. We also compare an aggregate model with a single elasticity to the benchmark model. Our main result from these counterfactual exercises is that sectoral heterogeneity does not always lead to an increase in the gains from trade, which is consistent with the theory.

**JEL Codes:** F10, F11, F14, F17

**Keywords:** gains from trade, estimated trade elasticities, simulated method of moments, sectoral heterogeneity, international price dispersion, multi-sector trade

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<sup>§</sup>We thank Lorenzo Caliendo, Fernando Parro, Bent Sorensen, Ina Simonovska, Michael Sposi, Jing Zhang, and especially Michael Waugh for very helpful discussions and comments. We also thank two anonymous referees for their comments. We thank Michael Waugh for sharing his SMM estimation codes with us. We thank participants at the Midwest International Trade Conference, York U., National U. of Singapore, the Atlanta Fed-Emory University International Economics Workshop, LSU, the Bank of Mexico, the 2018 Asia Meeting of the Econometric Society, and Union College for their comments. Heesuk Gloria Jung provided outstanding research assistance. The views expressed here are those of the authors and do not necessarily represent those of the Federal Reserve Bank of Dallas or the Federal Reserve System.

# 1 Introduction

Estimating the gains from international trade is one of the oldest and most important issues in economics. In recent years, owing to the development of easily accessible sectoral, bilateral trade and output data, as well as input-output tables, on the one hand, and tractable multi-sector, multi-country general equilibrium trade models on the other hand, there has been a surge in research quantifying the gains from trade.<sup>1</sup> In many of these studies, there is a presumption that increased sectoral heterogeneity leads to higher gains from trade. This presumption is natural: in a multi-sector model with Cobb-Douglas preferences across sectors in which the only source of heterogeneity across sectors is the initial sectoral trade shares, the multi-sector setting will always yield greater gains from trade, owing to Jensen’s inequality, than the aggregate version of this model (with the same parameters).<sup>2</sup>

However, there are many sources of sectoral heterogeneity in a typical multi-sector trade model. Trade elasticities, value-added shares of gross output, input-output linkages, and final demand shares, in addition to initial trade shares (driven by fundamental productivity and trade costs) can all vary across sectors. The gains from trade are a non-linear function of these parameters and variables. Ultimately, whether sectoral heterogeneity yields greater gains depends on whether, for example, sectors with high initial trade shares are also sectors with low value-added shares of gross output and strong input-output linkages. If so, sectoral heterogeneity will yield greater gains. However, if sectors with high initial trade shares are sectors with high value-added shares of gross output and low input-output linkages, sectoral heterogeneity will yield smaller gains. The goal of this paper is to quantitatively evaluate how sectoral heterogeneity affects the gains from trade in a systematic, comprehensive, and structurally consistent way.

We employ the [Caliendo and Parro \(2015\)](#) model, which embodies these forms of sectoral heterogeneity. Our calibrated model has 20 sectors and 21 countries, and we estimate and calibrate the parameters to match key features of the sectoral production, trade, ex-

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<sup>1</sup>See [Caliendo and Parro \(2015\)](#), [Ossa \(2015\)](#), [Costinot and Rodriguez-Clare \(2014\)](#), discussed later in the introduction, for example.

<sup>2</sup>If there are two sectors, both with a 0.5 expenditure share in the economy, and with domestic expenditure shares of 0.25 and 0.75, the ratio of the gains (relative to autarky) in the two-sector model relative to an aggregate model =  $2^{0.5} \frac{2}{3}^{0.5} > 1$ . See [Levchenko and Zhang \(2014\)](#) for a formal proof. The Cobb-Douglas preferences in the upper-tier is essential. See [Costinot and Rodriguez-Clare \(2014\)](#).

penditure and micro-price data. One of the main contributions of our paper is that we estimate the elasticity of trade with respect to trade costs for each of 19 traded sectors using the simulated method of moments (SMM) methodology of [Simonovska and Waugh \(2014a\)](#). Their methodology builds on an estimation methodology with micro price data introduced by [Eaton and Kortum \(2002\)](#), by correcting the bias from a small sample of price observations.<sup>3</sup> To our knowledge, this is the first application of the Simonovska and Waugh SMM estimator to estimate the trade elasticity at the sector level.<sup>4</sup> We use the Eurostat surveys of retail prices, which cover 12 OECD countries and 19 three-digit ISIC traded good sectors for 1990.<sup>5</sup>

Our sectoral trade elasticity estimates range from 2.97 to 8.94; the median is 4.38. We also estimate the sectoral trade elasticities with the original Eaton and Kortum (EK) method and the minimum, maximum, and median elasticities are 4.26, 35.55, and 10.29. So, our SMM estimates are clearly lower, as [Simonovska and Waugh \(2014a\)](#) obtained in their paper with a one-sector framework. In addition, as in [Simonovska and Waugh \(2014a\)](#) (hereafter, SW), the “bias” is larger the smaller the sample size. For example, ISIC 352, Other chemicals, has a sample size of 4, while ISIC 311, Food products, has a sample size of 343. Our SMM estimates are similar across these two industries, 3.75 and 3.57, respectively, but the EK estimates are 11.93 and 4.28, respectively. These estimates are used in our calibrated model. We calibrate the other parameters to match their data counterparts and/or to be consistent with sectoral outputs and trade flows.

With our calibrated model, we compute the gains from trade by comparing the welfare in our benchmark equilibrium relative to welfare in a counterfactual autarky equilibrium. Our benchmark calibrated model delivers gains from trade ranging from 0.40 percent in Japan to 8.33 percent in Ireland. The median gain in going from autarky to the calibrated equilibrium is 3.96 percent (Mexico). Our gains numbers tend to be considerably smaller than those in [Costinot and Rodriguez-Clare \(2014\)](#), in which the average gain is about 27 percent. Our welfare gains formula corresponds to the perfect competition, multi-sector,

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<sup>3</sup>[Eaton, Kortum, and Kramarz \(2011\)](#) also employ this type of estimator.

<sup>4</sup>[Simonovska and Waugh \(2014b\)](#) go further by showing that, given the data on trade flows and micro-level prices, different models have different implied trade elasticities and welfare gains.

<sup>5</sup>See [Crucini, Telmer, and Zachariadis \(2005\)](#), for example.

traded intermediate goods welfare gain formula in [Costinot and Rodriguez-Clare \(2014\)](#); hence, this difference in gains is primarily because our data are from 1990 and the [Costinot and Rodriguez-Clare \(2014\)](#) data are from 2008, and we employ our estimated elasticities, while [Costinot and Rodriguez-Clare \(2014\)](#) use the elasticities from [Caliendo and Parro \(2015\)](#).

We then conduct two sets of counterfactual exercises to assess the role of sectoral heterogeneity. We focus on five sources of heterogeneity in the gains from trade equation: sectoral trade elasticities, value-added gross output ratios, final demand shares, input-output linkages, and initial trade shares. In the first set of exercises, which we think of as “inspect the mechanism” exercises, we eliminate one or two sources of sectoral heterogeneity at a time. For each source of sectoral heterogeneity, we substitute a parameter (or variable) that is common across all sectors. For example, we replace the estimated sectoral trade elasticities with a single elasticity common to all sectors. We compute the gains from trade and compare these gains to those from the benchmark model. When we eliminate one source of heterogeneity at a time, we find that typically the gains from trade are close to that of the benchmark model. That is, when we replace our estimated sectoral trade elasticities with the median estimate (4.38), the sectoral value-added shares with the average value-added share, the sectoral final demand share with the average final demand share, the sectoral intermediate use requirements with an average intermediate use requirements, or the initial sectoral trade shares with a common average initial share share, the median (across countries) gains from trade are about 15 percent (equivalent to about one-half percentage point) higher or lower than the benchmark gains. For the value-added share case, the gains from trade are higher than in the benchmark model, and for the other four cases, the gains are lower than in the benchmark model. Our results for removing two sources of heterogeneity are similar. Notably, removing sectoral heterogeneity in the value-added share along with heterogeneity in one of the final demand share, the initial import share, or the trade elasticity, now leads to lower gains from trade than in the benchmark model, although the numbers continue to be relatively small. Overall, we find that most sources of sectoral heterogeneity lead to relatively small additional gains from trade.

In the second set of exercises, we compare the welfare gains in our benchmark model

to our aggregate model. The aggregate model has just one tradable sector; all heterogeneity across tradable sectors is eliminated. We also estimate the aggregate trade elasticity with the SW methodology; we obtain a value of 2.37. Owing in part to this low estimate, we find that the gains from trade in the aggregate model are about one-third larger than in the benchmark model. That is, when we compare our benchmark model with its estimated sectoral trade elasticities, and with sectoral heterogeneity on several other dimensions, to our aggregate model with its estimated aggregate trade elasticity and no sectoral heterogeneity across tradable sectors, it is the aggregate model that has greater gains from trade. Further investigation shows that the low estimated aggregate elasticity plays a key role. It is important to reiterate that both sets of elasticities are estimated in a model-consistent way.

To better understand the two sets of exercises, we construct 10-sector and 4-sector version of our models; we estimate the elasticities, and then we calculate the gains from trade. This exercise allows us to compare the estimated elasticities and the gains from trade as the number of sectors decrease in a sequence of models from the benchmark model to the aggregate model. In each successively more aggregate model, the average estimated elasticity is lower. We also find that the gains from trade broadly – albeit, not monotonically – increase as the models become more aggregated. These results put our above two exercises in context. The estimated elasticities matter the most for the gains from trade.

To further understand all of our results, we conduct a Monte Carlo-type exercise in which we simulate prices and trade shares from our calibrated benchmark model. We then aggregate across sectors, and ask: “suppose this data were generated from an aggregate model. What would be the implied aggregate trade elasticity?”. We find that the estimated aggregate elasticity from this exercise is about 2.65, which is only slightly larger than our actual estimated aggregate elasticity. In other words, our benchmark model generates data that would be consistent with a low aggregate elasticity in an aggregate model.

Overall, we conclude from our “inspect the mechanism” counterfactual, our benchmark vs. aggregate model counterfactuals, our additional exercises involving a smaller number of sectors, and our Monte Carlo exercise that increased sectoral heterogeneity does not necessarily imply larger gains from trade. This should not be a surprise, because it is just as the theory implies. The formula for the gains from trade shows clearly that whether sectoral

heterogeneity *per se* leads to greater gains depends on the interactions between the sectoral trade elasticities, initial trade shares, final demand shares, value-added shares of gross output, and the input-output linkages. Our results suggest that, overall, the interactions “cancel” to a large degree. A second conclusion is that model-consistent elasticity estimates should be used no matter the level of aggregation.

Our paper is most closely related to [Costinot and Rodriguez-Clare \(2014\)](#), and [Ossa \(2015\)](#). [Costinot and Rodriguez-Clare \(2014\)](#) and [Ossa \(2015\)](#) compare the gains from multi-sector models to the gains from one-sector models; these comparisons are similar to our second set of counterfactual exercises. However, crucially, they do not estimate their aggregate elasticity, and essentially use an average sectoral elasticity as their aggregate elasticity. These elasticities are larger than the median of their sectoral elasticities. We argue that there are good reasons to expect the “true” aggregate elasticity to be below the median sectoral elasticity – this is what we have found, and other research, notably [Broda and Weinstein \(2006\)](#), has found a similar pattern.

[Caliendo and Parro \(2015\)](#) also evaluate the gains from trade in multi-sector versus one-sector models in the context of the gains from NAFTA. They find that the multi-sector model delivers larger gains. A key reason may be that their estimated aggregate trade elasticity, 4.5, is close to their median estimated sectoral elasticity, while our estimated aggregate elasticity is about one-half our median estimated sectoral elasticity. [Levchenko and Zhang \(2014\)](#) is another related paper. The paper assesses the ability of simple gains from trade formulas to capture the gains from trade in a calibrated multi-country, multi-sector model. They find that the multi-sector formulas that allow for sectoral variation in trade shares, expenditure shares, and intermediate goods come closest to matching the calibrated model’s gains from trade. They also find that the multi-sector gains from trade formulas broadly imply larger gains from trade than their one-sector formulas. However, unlike in our paper, their analysis is conducted with a common  $\theta$  for all sectors.

Finally, our paper is related to several papers that address aggregation in the estimation of trade elasticities. [Broda and Weinstein \(2006\)](#) estimate their elasticities at several levels of aggregation, and obtain the same pattern as us – lower elasticities at higher levels of aggregation. [Imbs and Mejean \(2015\)](#) begin from a framework in which the aggregate

elasticity equals the mean sectoral elasticity by assumption. Then, under certain conditions, they show that there can be a downward bias in estimating the aggregate elasticity. However, in our framework, the starting point of [Imbs and Mejean \(2015\)](#) does not hold. [Feenstra, Luck, Obstfeld, and Russ \(2018\)](#) argue that instead of assuming that all home and foreign varieties have the same elasticity of substitution, a two-level aggregation of individual varieties within each country (micro elasticity), and then aggregation of the country bundles (macro elasticity), is preferred. They find that the upper level elasticity, the macro elasticity, is smaller than their micro elasticity, and both sets of estimates are on the order 3 or less.<sup>6</sup>

The rest of the paper is organized as follows. Section 2 lays out our model, and the following section provides our calibration and estimation methodology. Section 4 presents our trade elasticity estimates, and section 5 presents our benchmark welfare gains, and our counterfactuals. Section 6 concludes.

## 2 Model

Our model draws from [Alvarez and Lucas \(2007\)](#) and [Caliendo and Parro \(2015\)](#), (hereafter, CP) both of which extend [Eaton and Kortum \(2002\)](#), (hereafter, EK). Hence, we describe it briefly below, and where possible, we use the notation of CP and EK. There are  $N$  countries and  $S$  sectors, with  $S - 1$  sectors producing tradable goods, and one sector producing a non-traded good.

### 2.1 Production

In each tradable goods sector  $s \in S$  of country  $n \in N$ , there is a continuum of goods  $x_n^s \in [0, 1]$ . Each good is produced by combining labor and tradable and non-tradable intermediate inputs with a roundabout Cobb-Douglas technology:

$$q_n^s(x^s) = z_n^s(x^s) [l_n^s(x^s)]^{\gamma_n^s} \left[ \prod_{r=1}^S m_n^{r,s}(x^s)^{\xi_n^{r,s}} \right]^{1-\gamma_n^s} \quad (2.1)$$

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<sup>6</sup>Another related paper is [Yilmazkuday \(2019\)](#). This paper builds off of our paper, and addresses overcoming the paucity of data at the sectoral level to estimate elasticities. Its focus is on income elasticities with non-homothetic preferences, and on the heterogeneity of these elasticities across countries, not sectors.

where  $z_n^s(x^s)$  is the productivity or efficiency term and is drawn from a Fréchet distribution with country-sector specific productivity parameter  $\lambda_n^s$  and sector-specific variation parameter  $\theta^s$ .<sup>7</sup>  $l_n^s(x^s)$  is the labor used to produce good  $x^s$  in country  $n$ .  $\gamma_n^s$  is the value-added share of output in country  $n$  and sector  $s$ .  $m_n^{r,s}$  is the amount of sector  $r$  composite good used as an intermediate input for producing  $x^s$  in country  $n$ .  $\xi_n^{r,s}$  is the share of inputs from sector  $r$  used in the production of good  $x^s$  in country  $n$ ; it captures input-output linkages between sectors. Note that  $\sum_{r=1}^S \xi_n^{r,s} = 1$  for each sector  $s$ .

Given the above production function, and under perfect competition, the cost of a bundle of labor and intermediate inputs in each country-sector  $n, s$  is given by:

$$c_n^s = B_n^s V_n^s = B_n^s [w_n]^{\gamma_n^s} \left[ \prod_{r=1}^S (P_n^r)^{\xi_n^{r,s}} \right]^{1-\gamma_n^s}, \quad (2.2)$$

where  $w_n$  is the wage rate in country  $n$ ,  $P_n^r$  is the price of country  $n$  sector  $r$  composite intermediate, and  $B_n^s$  denotes a country-and-sector specific constant.<sup>8</sup>

For each country-sector  $n, s$ , individual goods are combined via a constant elasticity of substitution (CES) aggregator to make a sectoral composite good  $Q_n^s$ :

$$Q_n^s = \left[ \int_0^1 \bar{q}_n^s(x^s)^{\frac{\sigma-1}{\sigma}} dx^s \right]^{\frac{\sigma}{\sigma-1}} \quad (2.3)$$

where  $\bar{q}_n^s(x^s)$  is the amount of good  $x^s$  in country  $n$  used to produce the composite good, and  $\sigma$  is the elasticity of substitution between the individual goods in a sector. The composite good is used for consumption, and as an intermediate in the production of individual goods.

## 2.2 International Trade and Sectoral Prices

We make the standard iceberg assumption – in order for country  $n$  to receive one unit of a sector  $s$  good, country  $i$  must ship  $d_{ni}^s \geq 1$  units. Each country-sector will purchase the cheapest individual good, adjusted for trade costs. Owing to the Fréchet distribution of productivities, the sectoral price index is given by:

<sup>7</sup>The  $z$ 's are assumed to be independent across goods, sectors and countries.

<sup>8</sup> $B_n^s = (\gamma_n^s)^{-\gamma_n^s} (1 - \gamma_n^s)^{-(1-\gamma_n^s)} \left[ \prod_{r=1}^S (\xi_n^{r,s})^{-\xi_n^{r,s}} \right]^{(1-\gamma_n^s)}$



$$P_n^s = A^s \left( \sum_{i=1}^N (c_i^s d_{ni}^s)^{-\theta^s} \lambda_i^s \right)^{\frac{-1}{\theta^s}} \quad (2.4)$$

where  $A^s$  is a sector-specific constant.<sup>9</sup>

## 2.3 Consumption

In each country there is a representative household that derives utility from a final consumption good,  $C_n$ .

$$U_n = C_n \quad .$$

The final consumption good is a Cobb-Douglas aggregator of the sectoral composite goods used for consumption  $C_n^s$ .

$$C_n = \prod_{s=1}^S (C_n^s)^{\alpha_n^s} \quad (2.5)$$

where  $\sum_{s=1}^S \alpha_n^s = 1$  . The price of the final good, therefore, is given by

$$P_n = \prod_{s=1}^S (\alpha_n^s)^{-\alpha_n^s} (P_n^s)^{\alpha_n^s} \quad (2.6)$$

## 2.4 Market Clearing

We normalize labor in each country to 1. Then, the market clearing conditions for labor and the sectoral composite goods in country  $n$  are given by:

$$\sum_{s=1}^S \underbrace{\int_0^1 l_n^s(x^s) dx^s}_{l_n^s} \leq 1 \quad , n = 1, \dots, N \quad ,$$

$$\sum_{r=1}^S \underbrace{\int_0^1 m_n^{s,r}(x^s) dx^s}_{m_n^{s,r}} + C_n^s \leq Q_n^s \quad , n = 1, \dots, N \quad r, s = 1, \dots, S \quad .$$

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<sup>9</sup> $A^s = \left( \int_0^\infty u^{\theta^s(1-\sigma)} \exp(-u) du \right)^{\frac{1}{1-\sigma}}$  is a Gamma function.

## 2.5 Sectoral Expenditures, Trade Flows, Trade Balance, Labor Market Equilibrium, and Equilibrium in Changes

We define total per capita expenditure by country  $n$ , sector  $s$  as  $X_n^s = P_n^s Q_n^s$ . EK and CP show that the share of expenditure by country  $n$  on sector  $s$  goods from country  $i$  ( $D_{ni}^s$ ) is also the probability that country  $n$  will purchase a particular good in sector  $s$  from country  $i$ , ( $\pi_{ni}^s$ ) and is given by:

$$D_{ni}^s = \frac{X_{ni}^s}{X_n^s} = \pi_{ni}^s = \frac{\lambda_i^s [c_i^s d_{ni}^s]^{-\theta^s}}{\sum_{m=1}^N \lambda_m^s [c_m^s d_{nm}^s]^{-\theta^s}} \quad (2.7)$$

Using (2.4), we can rewrite this expression as:

$$D_{ni}^s = (A^s)^{-\theta^s} \left( \frac{c_i^s d_{ni}^s}{P_n^s} \right)^{-\theta^s} \lambda_i^s \quad (2.8)$$

It can be shown that total expenditure on the sector  $s$  composite good in country  $n$  is given by:

$$L_n X_n^s = \alpha_n^s w_n L_n + \sum_{r=1}^S (1 - \gamma_n^r) \xi_n^{s,r} \sum_{i=1}^N L_i X_i^r D_{in}^r \quad (2.9)$$

The equilibrium wage is determined by the balanced trade condition (2.10). The labor allocation in each sector (2.11) is implied by the firm's first order conditions:

$$\sum_{s=1}^S L_n X_n^s = \sum_{s=1}^S \sum_{i=1}^N L_i X_i^s D_{in}^s \quad (2.10)$$

$$L_n w_n l_n^s = \gamma_n^s \sum_{i=1}^N L_i X_i^s D_{in}^s \quad , \quad s = 1, \dots, S \quad (2.11)$$

The competitive equilibrium is the sectoral composite good price indices  $\{P_n^s\}_{s=1}^S$ , per capita expenditures on each sector's goods ( $\{X_n^s\}_{s=1}^S$ ), wages ( $w_n$ ), and labor allocations ( $\{l_n^s\}_{s=1}^S$ ),  $\forall n = 1, \dots, N$  that provide a solution to the system of equations - (2.4), (2.8), (2.9), (2.10), and (2.11).

As in CP, we solve the model employing the "changes" methodology developed by Dekle, Eaton, and Kortum (2008). Specifically, we solve for the changes in the endogenous

variables from changing trade costs  $d$  to  $d'$ , where  $d$  and  $d'$  represent the 3-dimensional matrix of country-by-country-by-sector trade costs. These changes can be characterized in “hat” form, in which, for example,  $\widehat{w} = \frac{w'}{w}$ . Please see Appendix A for the equations of equilibrium expressed in “hat” form.

## 2.6 Sources of Gains from Trade

What are the sources of gains from trade in our model with sectoral linkages? In our model, welfare is captured by the real wage; hence, the gains from trade is the change in the real wage in going from autarky to the current period. Using (2.6) yields the following expression for the real wage:

$$W_n = \frac{1}{\tilde{\alpha}} \prod_{s=1}^S \left( \frac{w_n}{P_n^s} \right)^{\alpha_n^s}, \quad (2.12)$$

where  $\tilde{\alpha} = \prod_{s=1}^S (\alpha_n^s)^{-\alpha_n^s}$ . Thus, real income is a geometric average of the real wage expressed relative to the price of sector  $s$  composite, with the weight being each sector’s weight in the final consumption good. Combining (2.8) with the expression for unit cost of the input bundle ( $c_n^s$ ) yields the following expression for  $w_n/P_n^s$  for the tradable goods sectors:

$$\frac{w_n}{P_n^s} = \left( \frac{1}{A^s B_n^s} \right)^{\frac{1}{\gamma_n^s}} \left( \frac{D_{nn}^s}{\lambda_n^s} \right)^{\frac{-1}{\theta^s \gamma_n^s}} \prod_{r=1}^S \left( \frac{P_n^r}{P_n^s} \right)^{\frac{-\xi_n^{r,s}(1-\gamma_n^s)}{\gamma_n^s}}, \quad s = 1, \dots, S$$

Note that the non-traded sector enters like the other sectors, except  $D_{nn}^s = 1$ . Substituting the above into the expression for the real wage gives:

$$W_n = \frac{w_n}{P_n} = \prod_{s=1}^S (\alpha_n^s)^{\alpha_n^s} \left[ \left( \frac{1}{A^s B_n^s} \right)^{\frac{1}{\gamma_n^s}} \left( \frac{D_{nn}^s}{\lambda_n^s} \right)^{\frac{-1}{\theta^s \gamma_n^s}} \prod_{r=1}^S \left( \frac{P_n^r}{P_n^s} \right)^{\frac{-\xi_n^{r,s}(1-\gamma_n^s)}{\gamma_n^s}} \right]^{\alpha_n^s} \quad (2.13)$$

Now, define  $\Psi_n^{r,s} = \xi_n^{r,s}(1-\gamma_n^s)$  as the  $(r, s)$  element of the  $(S \times S)$  matrix  $\Psi_n$ . Substituting (2.2) into (2.4) allows us to solve for sectoral prices as a function of  $w_n$ ,  $D_{nn}^r$ , and parameters.<sup>10</sup> Substituting this solution for prices into (2.13), we get:

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<sup>10</sup>In the absence of solving out for prices, our gains from trade equation is given by  $\ln \widehat{W}_n = \sum_{s=1}^S \left[ -\frac{\alpha_n^s}{\theta^s \gamma_n^s} \ln \widehat{D}_{nn}^s - \frac{\alpha_n^s (1-\gamma_n^s)}{\gamma_n^s} \sum_{r=1}^S \xi_n^{r,s} \ln \left( \frac{\widehat{P}_n^r}{\widehat{P}_n^s} \right) \right]$

$$W_n = \prod_{s=1}^S (\alpha_n^s)^{-\alpha_n^s} \left[ \prod_{r=1}^S (A^r B_n^r)^{-\tilde{\Psi}_n^{r,s}} (\lambda_n^r)^{\frac{1}{\theta^r} \tilde{\Psi}_n^{r,s}} (D_{nn}^r)^{-\frac{1}{\theta^r} \tilde{\Psi}_n^{r,s}} \right]^{\alpha_n^s} \quad (2.14)$$

where  $\tilde{\Psi}_n^{r,s}$  is the  $(r, s)$  element of the matrix  $(\mathbf{I}_n - \Psi_n)^{-1}$ . The matrix is the well-known Leontieff inverse, and we will refer to an individual element of it as the “input-output linkage”.

Then, the log change in the real wage is given by:

$$\ln \widehat{W}_n = - \sum_{s=1}^S \alpha_n^s \sum_{r=1}^S \frac{1}{\theta^r} \tilde{\Psi}_n^{r,s} \ln \widehat{D}_{nn}^r \quad (2.15)$$

Our welfare gain formula is essentially the same as that of CP and [Ossa \(2015\)](#), and it corresponds to equation 29 in [Costinot and Rodriguez-Clare \(2014\)](#) for the perfect competition case ( $\delta = 0$ ). There are four sources of gains from trade: the change in the domestic shares,  $D_{nn}^r$ ; the input-output linkages,  $\tilde{\Psi}_n^{r,s}$ ; the trade elasticities,  $\theta^r$ , and the final demand shares,  $\alpha_n^s$ . In response to a decline in trade barriers, the gains are larger, the more  $D_{nn}^s$  declines, and, for a given decline in  $D_{nn}^s$ , the larger is the input-output linkage,  $\tilde{\Psi}_n^{r,s}$ , the smaller is the trade elasticity,  $\theta^r$ , and the larger is the final demand share,  $\alpha_n^s$ . It is easy to see that the interaction of these sector-specific parameters and variables – sectoral heterogeneity – can matter. For example, the gains are larger to the extent that sectors with low trade elasticities are also sectors with high final demand shares and with large decreases in  $D_{nn}^s$ .

The input-output linkages terms,  $\tilde{\Psi}_n^{r,s}$ , embody value-added shares and cross-sector linkages, which, by themselves can play a key role in the welfare gains from trade. To understand their role, consider three cases. In the first case, suppose there are no intermediate goods; there is only value-added, i.e.,  $\gamma_n^s = 1$ . In this case,  $\Psi_n^{r,s} = 0 \forall r, s$ , and  $\tilde{\Psi}_n^{r,s} = 1$  if  $r = s$  and 0 otherwise. Hence, (2.15) reduces to  $-\sum_{s=1}^S \frac{\alpha_n^s}{\theta^s} \ln \widehat{D}_{nn}^s$ . In a value-added model, sectoral heterogeneity matters, but to a more limited extent than in (2.15). In the second case, there are intermediate goods and within sector input-output linkages, but no cross-sector linkages. In this case,  $\Psi_n^{r,s} = 1 - \gamma_n^s$ , and  $\tilde{\Psi}_n^{r,s} = \frac{1}{1 - \gamma_n^s}$ , if  $r = s$  and 0 otherwise.

The gains from trade are then given by:

$$-\sum_{s=1}^S \frac{\alpha_n^s}{\theta^s} \left( \frac{1}{1 - \gamma_n^s} \right) \ln \widehat{D}_{nn}^s. \quad (2.16)$$

It is easy to see that introducing intermediate goods in this way always leads to higher welfare gains than in the value-added model case. Also, all else equal, the smaller the value-added share, the higher the welfare gains. Comparing (2.16) to (2.15), we can see that adding cross-sector linkages adds numerous  $(S^2 - S)$  channels to the welfare gains. Some of these channels include non-traded goods. These goods influence the gains from trade via the cross-sector terms in  $\tilde{\Psi}_n^{r,s}$  that link  $\ln \widehat{D}_{nn}^s$  in the tradable sectors to the welfare gains.

Finally, it is important to indicate that despite, and because of, the richness of (2.15), it cannot be immediately inferred from that more sectoral heterogeneity automatically implies greater gains from trade. This is true for CP, Ossa (2015), and Costinot and Rodriguez-Clare (2014), and other papers that have similar welfare formulas. Whether there are greater gains from trade is a quantitative question that depends on the data and parameters. This is what we turn to now.

### 3 Calibration and Estimation Methodology

We now describe how we calibrate the model. We calibrate two versions of the model, which we call the “benchmark” model and the “aggregate” model. The aggregate model has just two sectors, a single tradable sector in which all the tradable sectors from the benchmark model are aggregated into one, and the non-traded sector.

The most important parameters to be calibrated are the sectoral  $\theta^s$ 's, which equal the trade elasticities with respect to trade costs, for each of the tradable sectors. We estimate the  $\theta^s$ 's by employing the simulated method of moments methodology introduced by Simonovska and Waugh (2014a) (hereafter, SW). The methodology builds on the method of moments methodology with micro price-level data introduced by EK. The EK estimator exploited a no-arbitrage condition to estimate trade costs. Essentially, with a sample of prices of individual goods comparable across countries, the trade cost between two countries must

not be less than any of the price differences for any good across that pair of countries. In other words, if the sample is large enough, the trade cost should equal the maximum price difference. However, in small samples, SW show that estimating trade costs in this way leads to upwardly biased estimates of the trade elasticity. SW develop a simulated method of moments (SMM) estimator to correct for that bias. To our knowledge, we are the first to apply this methodology at the sectoral level. The estimation procedure employs micro-level price data, categorized into sectors, and sectoral trade flow data, with the latter captured by a ‘gravity’ equation linking sectoral trade shares to source and destination fixed effects and to trade costs. In this section, we also describe our data sources, as well as the calibration of the other parameters.

### 3.1 Sector-Level Trade Elasticity

As stated above, we use the SMM estimation methodology developed by SW to estimate the trade elasticity for each tradable sector  $s - \theta^s$ . The two core estimating equations, as well as a summary of the methodology, are provided here; a detailed description is provided in Appendix C.

For two countries  $n$  and  $i$  and for sector  $s$ , we use (2.8) to obtain:

$$\frac{D_{ni}^s}{D_{ii}^s} = \frac{(A^s)^{-\theta^s} \left( \frac{c_i^s d_{ni}^s}{P_n^s} \right)^{-\theta^s} \lambda_i^s}{(A^s)^{-\theta^s} \left( \frac{c_i^s d_{ii}^s}{P_i^s} \right)^{-\theta^s} \lambda_i^s} = \left( \frac{P_i^s d_{ni}^s}{P_n^s} \right)^{-\theta^s}$$

In logs, we have:

$$\log \left( \frac{D_{ni}^s}{D_{ii}^s} \right) = -\theta^s \log \left( \frac{P_i^s d_{ni}^s}{P_n^s} \right) \quad (3.1)$$

Note that if we had only one sector, we would have  $\theta^s = \theta^{EK}$  where  $\theta^{EK}$  represents  $\theta$  in EK. Similar to EK and SW, we construct the sectoral prices, inclusive of trade costs, using micro price data:

$$\log \left( \frac{P_i^s d_{ni}^s}{P_n^s} \right) = \max_x \{r_{ni}(x^s)\} - \frac{\sum_{x=1}^{H^s} [r_{ni}(x^s)]}{H^s} \quad (3.2)$$

where  $r_{ni}(x^s) = \log p_n^s(x^s) - \log p_i^s(x^s)$ ,  $\max_x$  means the highest value across goods, and

$H^s$  is the number of goods in sector  $s$  of which prices are observed in the data. The above “trade elasticity” equation is one of the two core estimating equations.

We combine the above estimation with estimation of a structural gravity equation following EK and [Waug \(2010\)](#). Using, [\(2.8\)](#) we get:

$$\frac{D_{ni}^s}{D_{nn}^s} = \left( \frac{c_i^s d_{ni}^s}{c_n^s} \right)^{-\theta^s} \frac{\lambda_i^s}{\lambda_n^s}$$

Let  $\Omega_n^s = (c_n^s)^{-\theta^s} \lambda_n^s$  and  $T_n^s = \ln(\Omega_n^s)$ . Then

$$\ln \left( \frac{D_{ni}^s}{D_{nn}^s} \right) = T_i^s - T_n^s - \theta^s \ln(d_{ni}^s) \quad (3.3)$$

As in [Waug \(2010\)](#), we specify trade costs as follows:

$$\ln(d_{ni}^s) = \underbrace{dist_I}_{\text{distance}} + \underbrace{brdr}_{\text{border}} + \underbrace{lang}_{\text{language}} + \underbrace{tblk_G}_{\text{trade block}} + \underbrace{src_i^s}_{\text{source effect}} + \varepsilon_{ni}^s, \quad (3.4)$$

where  $dist_I$  ( $I = 1, \dots, 6$ ) is the effect of distance between  $n$  and  $i$  lying in the  $I$ th interval,  $brdr$  is the effect of  $n$  and  $i$  sharing a border,  $lang$  is the effect of  $n$  and  $i$  sharing a language,  $tblk_G$  ( $G = 1, 2$ ) is the effect of  $n$  and  $i$  belonging to a free trade area  $G$ , and  $src_i^s$  ( $i = 1, \dots, N$ ) is a source effect. The error term  $\varepsilon_{ni}^s$  captures trade barriers due to all other factors, and is assumed to be orthogonal to the regressors. The errors are assumed to be normally distributed with mean zero and variance,  $\sigma_\varepsilon$ . The six distance intervals (in miles) are:  $[0, 375)$ ;  $[375, 750)$ ;  $[750, 1500)$ ;  $[1500, 3000)$ ;  $[3000, 6000)$  and  $[6000, \text{maximum}]$ . The two free trade areas are the European Union (EU) and the North-American Free Trade Agreement (NAFTA).  $T_i^s$  is captured as the coefficient on source-country dummies for each sector  $s$ .

[\(3.1\)](#), [\(3.2\)](#), [\(3.3\)](#), and [\(3.4\)](#) are the core estimating equations in the SMM procedure. The procedure is now described:

1. Estimate  $\theta^s$  using trade and price data in [\(3.1\)](#) and [\(3.2\)](#) by the method of moments (MM) estimator as in EK. Call this  $\theta_{EK}^s$ .
2. Estimate [\(3.3\)](#) and [\(3.4\)](#). Because the data include zero-trade observations, we use the

Poisson pseudo maximum likelihood (PPML) estimation [Silva and Tenreyro \(2006\)](#). The gravity equation estimates provide measures of sector-source-destination trade costs conditional on a value for  $\theta^s$ .

3. For a given  $\theta^s$ , say,  $\theta_G^s$ , use source dummies in the gravity equation to estimate source marginal costs, and the coefficients on the trade cost measures to estimate bilateral trade costs.
4. Use the marginal cost and trade cost estimates to compute, for each good, the set of all possible destination prices. Select the minimum price for each destination. Repeat this exercise 50,000 times, corresponding to 50,000 goods in each sector.<sup>11</sup> These prices are the simulated prices.
5. Using all of the simulated prices, calculate the model-implied trade shares, and call them the simulated trade shares.
6. Draw goods prices – the actual number equals the number of goods in our sample (in the sector) – and trade shares from the pool of simulated prices and trade shares. Estimate  $\theta^s$  with the MM estimator. Call the estimate  $\theta_S^s$ . Repeat this exercise 1,000 times.
7. Find the  $\theta_G^s$  that minimizes the weighted distance between  $\theta_{EK}^s$  and the mean  $\theta_S^s$ . The selected  $\theta_G^s$  is the SMM estimate of  $\theta^s$ . Call this  $\theta_{SMM}^s$ .

Following [Eaton, Kortum, and Kramarz \(2011\)](#) and SW, we calculate standard errors using a bootstrap technique, taking into account sampling error and simulation error, as well as the fact that the right-hand side of (3.1) is a “generated regressor”. The latter, in particular, will deliver relatively high standard errors for those sectors with a small sample of goods. The procedure is discussed in detail at the end of Appendix C.

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<sup>11</sup>In SW, the total number of goods is 100,000. In our aggregate model, the number of goods is  $19 \times 50,000 = 950,000$ .



## 3.2 Data for Estimating Sectoral Trade Elasticities and Trade Costs

The data on prices of goods, needed for the estimation of sectoral  $\theta$ 's, come from Eurostat surveys of retail prices in the capital cities of EU countries for the year 1990. The data set has been compiled by [Crucini, Telmer, and Zachariadis \(2005\)](#) and used by [Giri \(2012\)](#) and [Inanc and Zachariadis \(2012\)](#), for example. We use price data for 12 countries included in the surveys - Austria, Belgium, Denmark, France, Germany, Greece, Ireland, Italy, Netherlands, Portugal, Spain and United Kingdom. The goods maintain a high degree of comparability across locations; typical examples of item descriptions are “500 grams of long-grained rice in carton”, or “racing bicycle selected brand”. The level of detail is for some cases at the level of the same brand sampled across locations. This enables exact comparisons across space at a given point in time. The retail price of a good in a given country is the average of surveyed prices across different sales points within the capital city of that country. Furthermore, the effect of different value added tax (VAT) rates across countries has been removed from the retail prices. The price data cover 1896 goods for the year 1990; we use 1410 of these goods prices. Each good is then assigned to one of our 19 ISIC sectors. We use the same assignment system as in [Crucini, Telmer, and Zachariadis \(2005\)](#).<sup>12</sup> For example, long-grained rice is assigned to sector 311 (Food products), and racing bicycle to sector 384 (Transport equipment). The sample size of prices in each sector ( $H^s$ ) is given in [Table 2](#).

In our framework, as is standard in EK-type multi-country models, we assume that within country trade and distribution costs are zero. To square this assumption with the reality of distribution costs, mark-ups, and other costs that make retail prices different from at-the-importing-dock prices, we assume, as do SW, that such costs have the same proportional effect on at-the-importing-dock prices across all goods.<sup>13</sup> Under this assumption, the solution of the model is identical to the one in which within country costs are zero.

Data on value-added, gross output and bilateral trade by sectors for 1990 come from the Trade, Production and Protection (TPP) database of the World Bank. They provide a broad

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<sup>12</sup>The data can be downloaded from <http://www.aeaweb.org/articles.php?doi=10.1257/0002828054201332>. See column V in the spreadsheets containing the price data.

<sup>13</sup>An alternative approach is to explicitly model such costs, as in [Giri \(2012\)](#)

set of data covering measures of trade, production and protection for 21 OECD countries and 28 manufacturing sectors corresponding to the 3-digit level International Standard Industrial Classification (ISIC), Revision 2.<sup>14</sup> Out of the 28 manufacturing sectors, we use data for 21 sectors, because, for the other sectors, there are many missing observations on trade flows. For the same reason, we also combine sectors 313 (Beverages) and 314 (Tobacco) into one sector, and sectors 341 (Paper and paper products) and 342 (Printing and Publishing) into another sector. The description of the 19 sectors is provided in the appendix in Table 9.<sup>15</sup> The data on trade barriers - distance, border and language - come from CEPII.<sup>16</sup>

To compute the trade shares for a sector  $s$  – share of country  $j$  in country  $i$ 's total expenditure on sector  $s$  goods – total exports of a country are subtracted from its gross output. This gives each country's home purchases for a sector ( $X_{ii}^s$ ). Adding home purchases and total imports of a country gives the country's total expenditure on sector  $s$  goods ( $X_i^s$ ). Normalizing home purchases and imports of an importing country from its trading partners by the importer's total expenditure creates the expenditure shares -  $D_{ij}^s$  - that are used in the gravity equation estimation.

### 3.3 Calibration of Other Parameters

In this section, we show how the other parameters of the model are calibrated. The value-added share of gross output in sector  $s$  and country  $n$ ,  $\gamma_n^s$ , is calculated for 1990 using data on value-added and gross output from the World Bank TPP database. We do this for all the tradable sectors. For the non-tradable sector, we use data for 1990 from the OECD STAN Structural Analysis database (STAN Industry, ISIC Rev. 2 Vol 1998 release 01). Our non-tradable sector consists of all sectors other than the manufacturing sector.

Two of our parameters,  $\xi_n^{r,s}$  – the share of sector  $r$  in the expenditure of sector  $s$  on intermediate inputs in country  $n$  – and  $\alpha_n^s$  – the sector  $s$  share of final domestic expenditure

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<sup>14</sup>The countries include Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Japan, Mexico, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, United Kingdom, and United States.

<sup>15</sup>Sectors dropped due to missing data on trade volumes are Industrial chemicals, Petroleum refineries, Miscellaneous petroleum and coal products, Non-ferrous metals, Machinery, except electrical, Professional and scientific equipment, and Other manufactured products.

<sup>16</sup><http://www.cepii.fr>

in country  $n$ , are calculated using the national input-output tables (NIOT) from the World Input-Output Database (WIOD). Specifically, we use the first year of the 2013 release, 1995, as a proxy for the tables in 1990. The sectors in these tables are concorded to match them with the ISIC categories for the price and other data. The concordance is described in Appendix B.

$\sigma$  is the elasticity of substitution between goods of a sector. EK shows that this parameter does not affect the results of the counterfactual exercises in our model. We choose  $\sigma = 2$  for all sectors.<sup>17</sup>

We set the trade elasticity ( $\theta$ ) for the non-traded sector to 4. As a reminder, in our aggregate model, the 19 traded goods sectors are combined into a single traded goods sector, and we continue to include the non-traded sector.<sup>18</sup> The parameters  $\gamma_n^s$ ,  $\alpha_n^s$ , and  $\xi_n^{r,s}$  for the single traded sector are constructed as weighted averages across the tradable sectors.

Table 1 shows the key parameters of our model averaged across countries.

**Table 1:** Average Across Countries of  $\gamma_n^s$  and  $\alpha_n^s$

ISIC Code	$\overline{\gamma_n^s}$	$\overline{\alpha_n^s}$
311	0.2603	0.0318
313,314	0.4911	0.0318
321	0.3878	0.0095
322	0.4269	0.0095
323	0.3296	0.0021
324	0.3925	0.0021
331	0.3565	0.0010
332	0.4150	0.0010
341,342	0.4285	0.0122
352	0.4421	0.0176
355	0.4380	0.0022
356	0.4085	0.0022
361	0.5829	0.0010
362	0.5003	0.0010
369	0.4512	0.0010
371	0.3391	0.0046
381	0.4180	0.0046
383	0.4176	0.0280
384	0.3469	0.0344
Non-tradable	0.6049	0.8027
Tradable (Aggregate Model)	0.3670	0.1973

<sup>17</sup>This is the highest value that ensures that the Gamma function determining  $A^s$  is well defined for all sectors.

<sup>18</sup>Hence, there is still an input-output structure, now with a 2 x 2 matrix.

## 4 Estimated Trade Elasticities

We present our estimated sectoral trade elasticities and our estimated aggregate trade elasticity, along with comparisons to the elasticities estimated by [Ossa \(2015\)](#), [CP](#), and [Broda and Weinstein \(2006\)](#).

### 4.1 Estimated Sectoral Trade Elasticities

Table 2 presents the results of the estimation of trade elasticities -  $\theta^s$ . The column labeled “SMM-PPML” shows the estimates from our application of the SW SMM methodology with PPML estimation of the gravity equation.<sup>19</sup> Bootstrapped standard errors for each estimate are in parentheses. For comparison, we also estimate the sectoral elasticities with the original Eaton and Kortum (EK) methodology. These estimates are in the column labeled “EK”. The last column shows the number of goods in each sector (after mapping the individual goods into the 3-digit ISIC sector categories).

Our sectoral trade elasticity estimates range from 2.97 (ISIC 341 and 342, Paper and products; printing and publishing) to 8.94 (ISIC 371, Iron and steel); and the median is 4.38 (ISIC 355, Rubber products). Our import-weighted average elasticity is 4.27, which is close to the median. The trade elasticity estimates with the EK methodology range from 4.26 (ISIC 383, Machinery, electric) to 35.55 (ISIC 372, Iron and steel) with a median of 10.29 (ISIC 324, Footwear, except rubber or plastic). In each sector, our SMM estimate of the trade elasticity is smaller than the estimate obtained by the EK methodology.

Hence, our SMM estimates mirror, at the sector level, what SW proved and demonstrated at the aggregate level. Moreover, we find, as expected based on SW, that the gap between our estimate and the EK estimate is smaller, the larger the number of goods per sector. In other words, the “bias” is smaller, the larger the sample size. For example, compare sectors 381 and 382. The former has just 11 observations, while the latter has 416. In the former, the SMM estimate is 5.07 and the EK estimate is 18.5, while in the latter, the SMM estimate is 3.27 and the EK estimate is 4.26.

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<sup>19</sup>We also estimated the elasticity by OLS. The estimates are very similar to the PPML estimates. This suggests that the issue of zeros in trade-flow data is not significant with our data.

Ossa (2015) estimates sectoral trade elasticities at the three-digit SITC level for 251 industries using methods pioneered by Feenstra (1994), and implemented recently by Broda and Weinstein (2006). The range of his estimates are [0.54, 24.05].<sup>20</sup> The mean estimate is 2.63; crucially, the median estimate is 1.91, which means, of course, that more than half of the estimated elasticities are less than 2. Overall Ossa’s sectoral elasticity estimates are considerably lower than our sectoral elasticity estimates. Ossa’s level of sectoral aggregation is also considerably lower than ours. Does this play a role? As we discuss later, Broda and Weinstein (2006) estimated sectoral trade elasticities at several levels of aggregation – they tended to find lower elasticities at higher levels of aggregation. This suggests that had Ossa estimated the elasticities at a level of aggregation similar to ours, the estimates might have been even lower than his existing estimates.

Caliendo and Parro (2015) also estimate structurally consistent sectoral trade elasticities. They use a triple-difference approach with sector-level data – sector-level tariff rates, in particular – to estimate their trade elasticities. Hence, their approach is quite different from ours. Their sectors are at roughly the same level of aggregation as ours, facilitating direct comparisons. Our three largest sectors in terms of final demand shares are Food, beverages and tobacco; Electric machinery; and Transport equipment. Our estimates for Food, and for Beverages and tobacco are both 3.57. CP’s estimate for the same sector is similar, 2.62 (all estimates listed here are with CP’s 99% sample). Our estimate for Electric machinery is 3.27, and CP’s estimates for Electric machinery and Communication equipment are 12.91 and 3.95, respectively, which are higher than ours. On the other hand, our estimate for Transport equipment is 4.47. CP’s estimates for Auto and Other Transport are 1.84 and 0.39, respectively, which are lower than ours. As suggested by these examples, our median elasticity, 4.38, is close to CP’s median elasticity, 3.965. However, our estimates exhibit a smaller range, [2.97, 8.94] than CP’s estimates for the manufacturing sectors, [0.39, 64.85]. Note that their lowest elasticity, as well as the lowest estimated elasticity in Ossa (2015), 0.54, are considerably smaller than our lowest estimated elasticity. This will be important for interpreting our welfare results vis-a-vis these other papers, which we discuss more fully below.

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<sup>20</sup>Ossa (2015) reports the estimates of the substitution elasticity,  $\sigma_s$ ; the trade elasticity is  $\sigma_s - 1$ .

To summarize, overall, our elasticity estimates have a higher median and a smaller range compared to those of [Ossa \(2015\)](#) and [Caliendo and Parro \(2015\)](#). In particular, our minimum sectoral elasticity is considerably higher than theirs.<sup>21</sup>

**Table 2:** Estimates of  $\theta^s$  (standard errors)

ISIC Code	Sector Description	SMM-PPML	EK	Sample Size of Prices
311	Food products	3.57 (0.28)	4.28	343
313,314	Beverages and Tobacco	3.57 (0.47)	5.36	93
321	Textiles	3.27 (0.59)	5.21	36
322	Wearing apparel, except footwear	4.41 (0.26)	5.17	143
323	Leather products	5.28 (0.48)	8.14	20
324	Footwear, except rubber or plast	4.77 (0.97)	10.29	20
331	Wood products, except furniture	4.17 (1.87)	15.45	8
332	Furniture, except metal	4.47 (0.88)	15.37	5
341,342	Paper and products and printing and publishing	2.97 (0.42)	6.57	14
352	Other chemicals	3.75 (0.51)	11.93	4
355	Rubber products	4.38 (0.58)	8.02	14
356	Plastic products	3.87 (2.24)	16.00	8
361	Pottery, china, earthenware	5.94 (2.81)	19.79	14
362	Glass and products	5.61 (1.60)	19.08	6
369	Other non-metallic mineral products	3.87 (1.34)	14.10	7
371	Iron and steel	8.94 (5.33)	35.55	16
381	Fabricated metal products	5.07 (2.46)	18.50	11
383	Machinery, electric	3.27 (0.52)	4.26	416
384	Transport equipment	4.47 (0.78)	6.50	232
	Minimum	2.97	4.26	4
	Maximum	8.94	35.55	416
	Average	4.51	12.08	74.21
	Median	4.38	10.29	14

<sup>21</sup>It is worth pointing that using the EK or SW methodologies, it would be difficult to obtain an elasticity estimate on the order of 1.5, for example. It is easy to see this for the EK methodology. From [\(3.1\)](#) and [\(3.2\)](#), we can see that the estimate for  $\theta^s$  is essentially the mean across country-pairs of the ratio of the log bilateral trade share and the maximum log bilateral price difference minus the average log bilateral price difference. It turns out that the average log bilateral price difference is very close to 0 in the data for most country-pair-sector combinations. Hence, given the log bilateral trade share in the data, the maximum log bilateral price difference is what determines the estimate for  $\theta^s$ . For example, in the Food products sector, for which the estimated elasticity is 4.28, the maximum log price difference translates into a factor 3.3 difference in prices. Consider the following question: given the log bilateral trade share in the Food products sector, what would the maximum price difference need to be if the EK estimate of  $\theta^s$  was 1.5? The maximum log price difference would be 3.4, which translate to a factor 30.4 difference in prices. This seems unlikely for our sample of countries.

## 4.2 Estimated Aggregate Trade Elasticity

As mentioned above, in our aggregate model, we combine the 19 traded goods sectors into a single aggregate traded sector (and still include the non-traded sector). In the CES aggregator for this sector, all goods are treated symmetrically; hence, in our estimation, we treat all goods symmetrically, as well. We obtain an estimate of  $\theta = 2.37$ . Two things stand out about this estimate. First, the estimate seems low relative to other aggregate estimates. Second, the estimate is lower than the minimum of our sectoral elasticity estimates. In the context of other aggregate elasticity estimates, it turns out there are estimates that are similar. For example, while EK's preferred estimate is 8.28, one of their estimates is 3.6. In addition, using EIU price data, which is closely related to our data, SW obtain an estimate of 2.82 with their SMM estimator. Finally, the aggregate elasticity that [Ossa \(2015\)](#) employs is 2.94; this is constructed as a trade-weighted cross-industry average of his estimated sectoral elasticities. (We return to the value of this elasticity in the next section.) These aggregate elasticity estimates are in the same ball park as ours.<sup>22</sup>

Why, then, is the aggregate elasticity estimate lower than all of the sectoral elasticity estimates? Conventional wisdom suggests that the aggregate elasticity should be some kind of weighted average of the sectoral estimates. However, for the estimation methodology we, SW, and EK use, this wisdom may not be correct. To explain this result, we first note that we estimate the aggregate tradable elasticity using the EK methodology and obtain  $\theta_{EK} = 2.64$ , which is also smaller than the minimum of the EK sectoral elasticity estimates (see Table 2). So, this result is not particular to the SMM methodology that SW develop and we employ. Hence, we focus on explaining the estimates with the (simpler) EK methodology.

As a reminder, the EK methodology employs a method of moments estimator based on one of the oldest economic principles, arbitrage. Referring back to (3.1), note that for a given value of the left-hand side, which we will loosely refer to as a trade share, and controlling for the sector-level price differences between countries, the estimated trade elasticity will be smaller, the higher the estimated trade cost. The reason for this is that a given trade share can be sustained via a high trade elasticity and a relatively low trade cost, or via a

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<sup>22</sup>[Head and Mayer \(2014\)](#) conducts a meta-analysis of estimated trade elasticities, and the median elasticity from structural gravity equations in 32 papers, out of 622 statistically significant coefficients, is 3.78.

low trade elasticity and a relatively high trade cost. Hence, for a given trade share, a low estimated elasticity arises because of a high estimated trade cost. In addition, the trade cost is estimated by the max price difference. This captures the arbitrage.<sup>23</sup> To summarize, a low trade elasticity arises, if all else equal, there are large max price differences.

Suppose for simplicity that all else is equal; in particular, all the sectoral trade shares are the same, and hence, the aggregate trade share equals the sectoral trade shares. In this case, variation in elasticity estimates comes about only because of variation in (the average across country-pairs of) the max price differences. When we go from a multi-sector setting, in which each country-pair-sector has its own max price difference, to an aggregate setting, in which for each country-pair there is just one max price difference (across all goods in all sectors), it should be clear that for each country-pair, the max price difference in the aggregate setting must be at least as large as any of the sectoral max price differences. Moreover, suppose there are one or more country pairs in which the max price difference in the aggregate setting is larger than the max price difference in the sector with the lowest  $\theta^s$ . Then, because no country-pair can have a smaller max price difference in the aggregate setting than in any one sector, including the sector with the lowest  $\theta^s$ , it must be the case that the method of moments estimator, which takes the average across country-pairs, will have a larger average max price difference in the aggregate case than in the sector with the lowest  $\theta^s$ . Hence, all else equal, the aggregate  $\theta_{EK} < \theta_{EK}^s \quad \forall s$ .

Returning to the simplifying assumption, we find empirically that, the left-hand side of (3.1) for the aggregate model, i.e., the aggregate trade share, is roughly equal to the average of the left-hand sides of (3.1) for the multi-sector model, i.e., the sectoral trade shares. Hence, the difference between the left-hand sides of (3.1) for the two models contributes little to the difference between the aggregate  $\theta$  estimate and the minimum sectoral  $\theta^s$  estimate. Rather, the result is driven by the combination of arbitrage and the method of moments estimator. Appendix D provides a version of the above discussion in terms of equations, building off of (3.2) and (3.1).

To summarize, the above discussion shows why the average max price difference across

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<sup>23</sup>The right-hand side of (3.2) also includes a term, the average price difference, to capture the sector-level price differences between countries. But, this term, when averaged across all country-pairs for the method of moments estimation, is essentially zero, and drops out.



country-pairs in the aggregate economy is larger than the average max price difference across country-pairs of any individual sector. Hence, measured trade costs in the aggregate economy will be higher than that of any individual sector. With these higher trade costs – and when the aggregate trade share is close to the mean of the sectoral trade shares – a given trade share can be rationalized only with an elasticity that is lower than the minimum of the sectoral elasticities.

We provide two additional interpretations of the low aggregate elasticity. First, in an aggregate model, there is just one trade cost. That cost must be consistent with all prices and price gaps (owing to arbitrage). These prices and price gaps are the source of the “discipline” in estimating the trade costs. Hence, in order to account for the large price gaps, a high trade cost will be the outcome, and given the trade share and the sector-level price indices, a high trade cost can be rationalized only via a low trade elasticity.

Second, in the multi-sector model, there are really two tiers of elasticities. The goods within a sector level are the lower tier and the relevant elasticity is across these goods for each sector. Our median sectoral elasticity is 4.38. The upper tier is the Cobb-Douglas aggregator of the sectoral consumption goods, in which the elasticity between the sectoral goods is, of course, 1. By contrast, in the aggregate model, there is just one elasticity between individual goods in the entire (tradable) economy. Hence, one way to interpret the aggregate elasticity is as an amalgam of the two tiers of elasticities.<sup>24</sup>

We also note that there is precedent for more aggregated elasticities to be lower on average (and on median) than the disaggregated elasticities. [Broda and Weinstein \(2006\)](#) is one example. The authors estimate elasticities at the ten-digit, SITC-5, and SITC-3 categorizations and the average (median) elasticities for the 1990-2001 period are 12 (3.1), 6.6 (2.7), and 4.0 (2.2), respectively. They interpret these results as consistent with a view that varieties are less substitutable at higher levels of aggregation. We conduct a similar exercise by aggregating our 19 sectors to 10 sectors, and also to 4 sectors.<sup>25</sup> Appendix F gives our aggregation scheme. When we aggregate to 10 sectors, the range, average, and median of the estimates are now [2.97, 5.67], 4.00, and 3.84, respectively. When we aggregate to 4

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<sup>24</sup>We thank the editor for suggesting this interpretation.

<sup>25</sup>When we aggregate we maintain the size of the pool of goods at 50,000, but our sample size that we draw from is now the sum of the samples of the sectors that are aggregated.

sectors the range, average, and median of the estimates are now tight [3.24, 3.57], 3.41, and 3.42. So, as we aggregate our sectors, the elasticities become smaller, exactly as in [Broda and Weinstein \(2006\)](#). Section 5.2.3 provides GFT calculations for the 10-sector and 4-sector models. As will be seen, there is not a monotonic relationship between the median or average elasticity and the GFT; this provides evidence that the GFT are not driven solely by the estimated elasticities.

## 5 Welfare Gains from Benchmark Model and from Sectoral Heterogeneity

We now report the welfare gains from our benchmark model; we then present our results from two sets of counterfactual exercises on sectoral heterogeneity and the gains from trade.

### 5.1 Welfare Gains of Benchmark Multi-Sector Model

In implementing the “changes” methodology of [Dekle, Eaton, and Kortum \(2008\)](#), we use our estimated  $\theta^s$ 's, the other calibrated parameters described in section 3.3, and the empirical values of  $D_{ni}^s$  for all country-pair-sectors and of  $w_n$  for all countries, as our baseline. We then feed into the model a 100 times increase in trade costs and compute the change in welfare from the baseline economy ( $\widehat{W}_n$  from (2.15)). We interpret  $1 - \widehat{W}_n$  as the change in welfare in going from autarky to the actual economy in 1990, i.e., the gains from trade.<sup>26</sup>

The gains from trade are given in Table 3. The welfare gain ranges from 0.40% for Japan to and 7.51% for Netherlands with a median (mean) gain of 3.96% (4.05%). The gains for small countries are about an order of magnitude larger than for the largest countries. These gains are of similar magnitude to those in EK, for example.

We find that, in most countries, only a few sectors account for most of the welfare gains from trade. For example, in the United States, sectors 383 (machinery, electric) and 384 (transport equipment) account for almost 90% of the gains. These two sectors, along with sectors 341 (paper products and publishing) and 311 (food products) account for the

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<sup>26</sup>We solve the model using the algorithm developed by Alvarez and Lucas (2007).

majority of the gains from trade in most countries. By and large, these are the sectors which are experiencing the highest trade flows, as captured by  $-\widehat{D}_{nn}$ . That said, there is considerable heterogeneity across countries in the importance of particular sectors to the gains from trade. Thus, comparative advantage at the sector-level is an important factor determining the welfare gains from trade. Our results here are consistent with [Ossa \(2015\)](#), who finds with more disaggregated data that 10 percent of the industries account for 90 percent of the gains.

To summarize our results in this section, we find that variation in the gains from trade lines up well with economic size, and that only a few sectors account for most of the gains from trade.

**Table 3:** Welfare Gains from Trade: Benchmark Model

Country	Gains from Trade (percent)
AUS	2.11
AUT	4.90
BLX	6.40
CAN	3.87
DEU	1.91
DNK	5.57
ESP	2.32
FIN	3.94
FRA	2.10
GBR	2.76
GRC	4.67
IRL	8.33
ITA	3.09
JPN	0.40
MEX	3.96
NLD	7.51
NOR	5.53
NZL	4.13
PRT	5.95
SWE	4.66
USA	1.03
Average	4.05
Median	3.96
Max	8.33
Min	0.40

## 5.2 Role of Sectoral Heterogeneity

Our theoretical framework has six sources of sectoral heterogeneity – trade elasticities, input-output structure, value-added shares, final demand shares, trade costs, and productivities. Of these, the first four show up directly in the gains from trade equation (2.15), and the latter two show up primarily through the initial trade share  $D_{nn}^s$ . To assess the importance of this heterogeneity in the gains from trade, we conduct two sets of counterfactuals.

The first set of counterfactuals starts from the benchmark model, and then replaces one source of sectoral heterogeneity with a single parameter common to all tradable sectors. For example, to assess the importance of heterogeneity in the sectoral value-added shares of gross output  $\gamma_n^s$ , we replace all of the sector level  $\gamma_n^s$ 's with a single  $\gamma_n$  common to all tradable sectors (but still country-specific). All other sources of heterogeneity are unchanged. We do this exercise for the value-added shares, the final demand shares, the input-output shares, and the trade elasticity, one at a time. We also study the effects of replacing two sources of sectoral heterogeneity.<sup>27</sup> These counterfactuals address the role of specific model mechanisms, i.e., “inspect the mechanism”, and in so doing, answer the question: What is the role of sectoral heterogeneity in a particular parameter or variable in driving the gains from trade?

The second set of counterfactuals compares our calibrated benchmark model to our calibrated aggregate model, in which each of the five sources of sectoral heterogeneity is replaced with a single, aggregate value (covering all the tradable sectors). In particular, as discussed above, the aggregate model includes our estimate for the aggregate trade elasticity. This set of counterfactuals provides a comprehensive look at the importance of sectoral heterogeneity, and addresses the following question: Does a calibrated multi-sector model yield greater gains from trade than a calibrated aggregate model? These counterfactuals are most similar to those in [Ossa \(2015\)](#), [CP](#), and [Costinot and Rodriguez-Clare \(2014\)](#).<sup>28</sup>

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<sup>27</sup>We note that for all of the counterfactuals that do not involve the trade elasticity, we do not re-estimate the trade elasticities.

<sup>28</sup>Owing to our use of the [Dekle, Eaton, and Kortum \(2008\)](#) “changes” methodology, which starts from the baseline data, all of our counterfactuals are trivially consistent with the baseline data.

### 5.2.1 Importance of Individual Sources of Sectoral Heterogeneity

We start by examining the role of heterogeneity in the sector-level value-added shares of gross output in tradable sectors,  $\gamma_n^s$ 's. Specifically, for each country, we replace the sector-specific value-added share for every tradable sector with the country's overall tradable value-added share. The range across countries of the common  $\gamma_n$  across tradable sectors is  $[0.29, 0.47]$ . The welfare gains for this counterfactual are listed in column 3 of Table 4, i.e., the column labeled 'BM1'. The table shows that the GFT with a common value-added share across sectors are typically higher than in the benchmark case. Sectoral heterogeneity in  $\gamma_n^s$  does not lead to higher GFT; rather, it leads to lower GFT. Equation (2.15) illustrates what is needed for the benchmark model to have higher GFT: sectors with low  $\gamma_n^s$  (and hence high  $\tilde{\Psi}_n^{s,s'}$ ) should also be sectors with relatively low  $\theta^s$ , high  $\alpha_n^s$ , and large  $\ln \hat{D}_{nn}^s$ . Evidently, this is not the case. That said, it is worth noting that the benchmark model gains are only slightly lower than in BM1.<sup>29</sup>

**Table 4:** Gains from Trade (percent)

Country	BM	BM1	BM2	BM3	BM4	BM5
AUS	2.11	2.15	1.90	2.04	1.67	1.87
AUT	4.90	4.94	4.64	4.77	4.34	4.63
BLX	6.40	6.56	5.95	6.26	1.31	6.11
CAN	3.87	3.88	2.92	3.39	3.26	3.54
DEU	1.91	1.91	1.76	1.88	1.80	1.85
DNK	5.57	5.96	5.87	5.60	4.02	5.54
ESP	2.32	2.35	2.03	2.24	2.38	2.13
FIN	3.94	4.21	3.85	3.94	3.27	3.53
FRA	2.10	2.11	1.86	1.99	1.95	1.94
GBR	2.76	2.80	2.51	2.69	2.70	2.46
GRC	4.67	4.41	4.57	4.78	4.86	4.44
IRL	8.33	8.93	8.44	8.39	5.76	7.81
ITA	3.09	3.13	2.69	3.05	3.07	2.79
JPN	0.40	0.40	0.37	0.40	0.34	0.35
MEX	3.96	3.88	3.68	3.56	3.41	3.42
NLD	7.51	7.62	7.32	7.57	6.41	7.07
NOR	5.53	5.81	6.06	5.36	4.03	5.35
NZL	4.13	4.13	3.59	3.81	2.86	3.93
PRT	5.95	5.94	4.67	5.58	4.84	5.69
SWE	4.66	4.83	5.01	4.65	3.78	4.22
USA	1.03	1.04	0.84	0.96	0.93	0.95

<sup>29</sup>We also consider a scenario in which  $\gamma_n^s = \bar{\gamma}_n^s = 0.367 \forall n, s$ . This value is the average across all countries and tradable sectors of the value-added gross output ratio. The GFT were higher than in column BM1. For example, the U.S. GFT was 1.15%.

Average	4.05	4.14	3.83	3.95	3.19	3.79
Median	3.96	4.13	3.68	3.81	3.26	3.54
Max	8.33	8.93	8.44	8.39	6.41	7.81
Min	0.40	0.40	0.37	0.40	0.34	0.35

BM: Benchmark model; BM1: benchmark model with same  $\gamma_n^s$  across tradable sectors  $s$ ; BM2: benchmark model with same  $\alpha_n^s$  across tradable sectors; BM3: benchmark model with same  $\xi_n^{r,s}$  across tradable sectors; BM4: benchmark model with same trade share  $D_{ni}^s$  across tradable sectors; BM5: benchmark model with median sectoral  $\theta^s$ ;

Next, we study the effects of a common final demand (domestic expenditure) share  $\alpha_n^s$  for each country across all its sectors. For each country, we take the sum across all tradable sectors of the final domestic expenditure share, which is equivalent to 1 minus the non-traded final domestic expenditure share, and divide by the number of tradable sectors. We use this value for all the tradable sectors in a country. The range across countries of the common  $\alpha_n^s$  across tradable sectors is  $[0.0085, 0.016]$ . The GFT results are given in column 4 of Table 4, i.e., the column labeled ‘BM2’. The table shows that in all but four countries, the GFT in the benchmark model are higher than for this scenario. However, the gains for having sectoral heterogeneity in final demand are slight. This is because, with sectoral heterogeneity in  $\alpha_n^s$ , more weight is given to sectors like ISIC 383, 384, 311 and 312. However, for most countries, these sectors have  $\theta_n^s$ ’s and  $\gamma_n^s$ ’s that are close to the economy-wide average. Hence, the additional heterogeneity does not deliver significant additional gains.<sup>30</sup>

We also study the effects of sectoral heterogeneity in the input-output structure. We impose a common input-output “use” structure across tradable sectors. In other words, for each country-sector  $n, r$ , we set the  $\xi_n^{r,s}$  to be the same  $\forall$  tradable  $s$ . The values are the average across all tradable columns. For example,  $\xi_{U.S.}^{384,s} = 0.025 \forall$  tradable  $s$ , which means, that in the United States, the output of ISIC 384 (transport equipment) is used with the same intensity as an input in all tradable sectors. The GFT results are given in column 5 of Table 4, i.e., the column labeled ‘BM3’. The table shows that the welfare gains from a model with a common input-output structure are smaller than in the benchmark case, although, again, the differences are small.<sup>31</sup>

<sup>30</sup>We also consider a scenario in which  $\alpha_n^s = \overline{\alpha_n^s} = 0.010 \forall n, s$ . This value is the average across all countries and tradable sectors of the final demand share. The GFT were slightly higher than in column BM2. For example, the U.S. GFT was 0.94%.

<sup>31</sup>We also study a scenario in which every country has the same “use” structure across tradable sectors and countries. In other words, starting from the exercise in BM3, we set the  $\xi_n^{r,s}$  to be the same  $\forall$  tradable

We next study the effects of heterogeneity in initial import shares  $D_{ni}^s$ . For each country  $n$ , we replace  $D_{ni}^s$  in every tradable sector with the average across all tradable sectors of  $D_{ni}^s$ . The GFT results are given in column 6 of Table 4, i.e., the column labeled ‘BM4’. Overall, the average and median GFT are 3.2% and 3.3%, respectively, which are about 20-25 percent lower than their counterparts in the benchmark model. In other words, sectoral heterogeneity in the tradable  $D_{ni}^s$  leads to greater GFT. Moreover, the benchmark model’s GFT “gap” is larger than with any other source of heterogeneity.

Next, we examine the role of heterogeneity in the elasticity of trade  $\theta^s$ . A key issue in this exercise is the value of the single elasticity. In this subsection, we have focused on using averages as the metric for the absence of heterogeneity, so for  $\theta^s$ , we use the median of our sectoral theta estimates, which is 4.38. (Note, that in the next sub-section we should not use a median, but the actual estimated aggregate elasticity.) Column 7 of table 4, i.e., the column labeled ‘BM5’, shows the gains from trade (GFT) when all the sectoral  $\theta^s$ ’s are replaced by the median sectoral  $\theta^s$ . Comparing this column to column 2 (BM), it can be seen that the GFT are lower than in the benchmark model, i.e., heterogeneity in sectoral  $\theta^s$ ’s leads to higher GFT. Again, however, the differences are not large. For example, the median GFT is 3.54% in column 7 and 3.96% in the benchmark model. We can see why the gap is small by returning to (2.15). Heterogeneity in  $\theta^s$  will lead to larger gains from trade to the extent that  $\theta^s$  is small when  $\gamma_n^s$  is small (and hence  $\tilde{\Psi}_n^{s,s'}$  is large),  $\alpha_n^s$  is large, and  $\ln \hat{D}_{nn}^s$  is large. It turns out that for most countries, ISIC 383 and 384 (electric machinery and transport equipment) are the two sectors in which both  $\ln \hat{D}_{nn}^s$  and  $\alpha_n^s$  are both large. However, both sectors have a  $\theta^s$  that is close to the median value. Moreover, in most countries, these sectors’ value-added shares,  $\gamma_n^s$ , are close to the average across sectors of  $\gamma_n^s$ . Hence, for these two sectors, which are the major sources of the gains from trade for most of the countries, replacing the sector-specific  $\theta^s$  with the median  $\theta^s$  changes the gains from trade by very little. This is the main reason why the GFT in the benchmark model are only slightly larger than the GFT in the exercise with the median sectoral  $\theta$ .<sup>32</sup>

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$s$  and  $\forall n$ . We take a simple average across countries of the  $\xi_n^{r,s}$  we used in BM3. The GFT are slightly lower than in BM3. For, example, the U.S. GFT was 0.92%.

<sup>32</sup>We also run counterfactuals with alternative common sectoral elasticities, including the median of CP’s estimates, 4.49, SW’s preferred estimate, 4.14, and EK’s preferred estimate, 8.28. As expected, those counterfactuals in which the common elasticity is close to our median sectoral elasticity will yield GFT close

As an additional exercise, we compare the GFT in our benchmark model in which our estimated sectoral elasticities are replaced by the CP (99% sample) estimated sectoral elasticities, to the GFT in our benchmark model in which our estimated sectoral elasticities are replaced by the median CP sectoral elasticity. In other words, we conduct the same comparison as in the previous paragraph except with CP’s sectoral elasticities. We find the same pattern that the benchmark model with the sectoral elasticities has greater GFT than the same model with the median sectoral elasticity; however, quantitatively, the gap is larger in this case than with our elasticities. For example, the median GFT for the model with CP’s sectoral elasticities is 4.99%, while it is 3.46% in the model with CP’s median elasticity.<sup>33</sup>

We study the effects of removing two sources of sectoral heterogeneity at a time, focusing on the value-added share of gross output,  $\gamma_n^s$ ; the final demand share,  $\alpha_n^s$ ; the initial import share,  $D_{ni}^s$ ; and the trade elasticity,  $\theta^s$ . The results are given in Appendix E. They show that removing two sources of heterogeneity does lead to lower GFT than in our benchmark model, although the difference continues to be small – the average across all countries and scenarios is about one-half of one percentage point. Notably, removing sectoral heterogeneity in  $\gamma_n^s$  along with heterogeneity in one of the final demand share, the initial import share, or the trade elasticity, now leads to lower GFT than in the benchmark model. Recall that removing heterogeneity in  $\gamma_n^s$  alone led to higher GFT than in the benchmark model. Overall, our results are consistent with the interpretation that how the different terms in (2.15) matters for the importance of sectoral heterogeneity in the GFT.

To summarize, we have found that removing one source of sectoral heterogeneity typically yields smaller gains from trade than in our benchmark model. However, the differences are on the order of a half percentage point (against a median GFT in our benchmark model of about 4 percent). We conclude that our “inspect the mechanism” exercises show that sectoral heterogeneity has little effect on the gains from trade.<sup>34</sup>

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to that in column BM1, but the counterfactual with the EK estimate leads to GFT that are about half that in column BM1. For example, the GFT for the United States are 0.92%, 1.00%, and 0.50%, respectively.

<sup>33</sup>The mapping from CP’s sectoral elasticities to our 19 ISIC sectors is as follows: Food products: 2.62; Beverages and Tobacco: 2.62; Textiles: 8.1; Wearing apparel: 8.1; Leather products: 8.1; Footwear: 8.1; Wood products: 11.5; Furniture 11.5; Paper and printing: 16.52; Other chemicals: 3.13; Rubber products: 1.67; Plastic products: 1.67; Pottery: 2.41; Glass products: 2.41; Other non-metallic mineral products: 2.41; Iron and steel: 3.28; Fabricated metal products: 6.99; Electric machinery: 12.91; and Transport equipment: 1.84.

<sup>34</sup>It is worth reiterating that each of these counterfactual exercises focuses on removing heterogeneity in



### 5.2.2 Benchmark Model vs. Aggregate Model

This section presents the second set of counterfactuals. As discussed above, we calibrate and estimate an aggregate model with just one tradable sector (and one non-tradable sector). Hence, each of the five sources of sectoral heterogeneity (across tradable sectors) is eliminated, including the trade elasticity. Columns 2 and 3 of Table 5 show the GFT for the benchmark model and the aggregate model, respectively. With the exception of Belgium-Luxembourg, the gains are typically larger with the aggregate model. The median gain is about 35%, or about 1.4 percentage points, larger than in the benchmark model. The direction of the effect is a key result: the benchmark model, with its model-consistent estimates of sectoral trade elasticities and its five sources of sectoral heterogeneity, yields lower gains from trade than the aggregate model, with its model-consistent estimate of the aggregate trade elasticity, and no sources of tradable sectoral heterogeneity.

We devote the rest of this sub-section and the next sub-section to explaining and discussing this result, especially in the context of CP, [Ossa \(2015\)](#), and [Costinot and Rodriguez-Clare \(2014\)](#). Even though there are five sources of heterogeneity, we first show that one source, the trade elasticities, plays a key role. A central factor is the elasticities of trade in the multi-sector benchmark model relative to the elasticity of trade in the one-sector model. As discussed in section 4.2, our sectoral trade elasticities are higher than our aggregate elasticity, while in these other three papers, the aggregate elasticity is higher than the median of their sectoral trade elasticities.

To see the importance of this in the context of our model, we conduct a counterfactual simulation in which we replace the sectoral elasticities in our benchmark model with our aggregate elasticity, and then compute the gains from trade. These are illustrated in column 4 of Table 5, labeled “BM7”. The gains from trade are now about 20 – 30% larger than in the aggregate model. Hence, once we give the benchmark model the same elasticity for each sector, i.e., the aggregate elasticity, then the benchmark model has higher GFT than the

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the tradable sectors. Looming large in our model is the non-traded sector, which accounts for the majority of value-added in each country, and the the largest input share for most country-sectors’ output. If, for example, we repeated the exercise in BM3, but also included the non-traded sector, the GFT results would have averaged about 30% larger than in the benchmark model. So, this would be a case in which less heterogeneity would lead to larger gains from trade. We find a similar pattern of results when we remove two sources of sectoral heterogeneity at a time.

aggregate model. Only then does sectoral heterogeneity along four dimensions (all but the sectoral trade elasticity) deliver greater GFT.

**Table 5:** Gains from Trade (percent)

Country	BM	Agg	BM7	Agg1
AUS	2.11	2.78	3.43	1.51
AUT	4.90	7.16	8.39	3.94
BLX	6.40	2.20	10.99	1.20
CAN	3.87	5.37	6.45	2.94
DEU	1.91	3.02	3.39	1.65
DNK	5.57	6.59	10.00	3.62
ESP	2.32	3.99	3.90	2.18
FIN	3.94	5.36	6.43	2.94
FRA	2.10	3.23	3.56	1.76
GBR	2.76	4.39	4.49	2.40
GRC	4.67	7.20	8.06	3.96
IRL	8.33	9.25	13.96	5.12
ITA	3.09	5.14	5.09	2.81
JPN	0.40	0.59	0.65	0.32
MEX	3.96	5.67	6.22	3.11
NLD	7.51	10.11	12.67	5.60
NOR	5.53	6.83	9.66	3.76
NZL	4.13	4.68	7.14	2.56
PRT	5.95	7.90	10.27	4.36
SWE	4.66	6.24	7.66	3.42
USA	1.03	1.52	1.74	0.83
Average	4.05	5.20	6.86	2.86
Median	3.96	5.36	6.45	2.94
Max	8.33	10.11	13.96	5.60
Min	0.40	0.59	0.65	0.32

BM: Benchmark model; Agg: Aggregate Model; BM7: benchmark model with aggregate  $\theta$ ; Agg1: Aggregate model with median sectoral  $\theta^s$

We conduct another counterfactual exercise, in which we replace the aggregate elasticity from the aggregate model with the median sectoral elasticity from the benchmark model. This exercise corresponds most closely to the one in [Ossa \(2015\)](#) and [Costinot and Rodriguez-Clare \(2014\)](#). The results are shown in column 5 of [Table 5](#), “Agg1”. Here we see that the GFT in the benchmark model are about 30%, or 1 percentage point, higher than in this version of the aggregate model.<sup>35</sup> Hence, qualitatively, we obtain the same result as [Ossa](#) and as [Costinot and Rodriguez-Clare](#).<sup>36</sup>

<sup>35</sup>If we use the median CP elasticity, the GFT are virtually identical to those in “Agg1”.

<sup>36</sup>Our quantitative results in this exercise are not as stark as those of [Ossa \(2015\)](#) and [Costinot and Rodriguez-Clare \(2014\)](#). This can be explained by the fact that in the multi-sector models, much of the GFT

We conduct one other comparison. We compare our benchmark model with the median sectoral elasticity (“BM4” in Table 4) with the aggregate model with the median sectoral elasticity (“Agg1” in Table 5). The GFT in the benchmark model are about 25%, or about 0.9 percentage points, higher than in the aggregate model. This exercise is analogous to, and yields similar results as, the one in [Levchenko and Zhang \(2014\)](#).

### 5.2.3 Discussion

The preceding two sub-sections come at the question of the importance of sectoral heterogeneity for the GFT from opposite sides. One starts with the benchmark model and removes one source of heterogeneity at a time. As the results in Table 4 show, removing one source of heterogeneity typically reduces the GFT, but slightly. The second starts with the benchmark model and removes all sources of sectoral heterogeneity – this is our aggregate model. As Table 5 shows, here, the GFT are higher in the aggregate model than in the benchmark model. Further investigation shows that a key role is played by the estimated aggregate elasticity, which is low relative to the estimated sectoral elasticities. We reiterate that for the aggregate model, we estimate the model-consistent aggregate elasticity. If a median sectoral elasticity is used instead of the estimated model-consistent elasticity, then the GFT in the benchmark model are higher than in the aggregate model, which is a result similar to what [Ossa \(2015\)](#) and [Costinot and Rodriguez-Clare \(2014\)](#) obtain.

As we have stated above, we believe the appropriate comparison between the benchmark model and the aggregate model should involve model-consistent values of all the parameters and exogenous variables. Regarding the trade elasticity, the model treats all goods within a sector, or within the aggregate economy, as symmetric. This is how we treat the goods in the estimation of the elasticities. And, as we have shown, these elasticity estimates play a critical role.

Neither [Costinot and Rodriguez-Clare \(2014\)](#) nor [Ossa \(2015\)](#) uses a model-consistent 

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is driven by the sectors with the lowest elasticities. In Ossa’s multi-sector model, a number of elasticities are close to and even less than 1. All else equal, an elasticity of 1 delivers 10 times the gains from trade as an elasticity of 10. Put differently, the gains in a world with two sectors with elasticities of 1 and 10 will be several times larger than the gains in a world with two sectors with elasticities both equal to 5. Indeed, [Ossa \(2015\)](#) shows that just 10 percent of the industries account for 90 percent of the gains. In private correspondence, Ossa indicated that these industries were largely the industries with the lowest elasticities. We thank Ossa for this correspondence.

estimate of the aggregate elasticity. In both papers, the aggregate elasticity that is used is greater than the median of the sectoral elasticities. The former paper uses 5 as the aggregate elasticity, drawn from [Head and Mayer \(2014\)](#), while the median of their multi-sector elasticities (which come from CP) is 3.965. The latter paper calculates a trade-weighted average of the sectoral elasticities, and obtains an aggregate trade elasticity, 2.94, that is considerably larger than the median of the sectoral trade elasticities, 1.91. It should be noted, however, that there is no theoretical reason to use a trade-weighted average. Our counterfactual exercises above suggest that this elasticity “gap” is an important reason why the GFT are larger in their multi-sector models compared to their aggregate models. We also believe there are good reasons to expect the gap to be smaller, if not reversed, if model-consistent estimates are used.

For example, Ossa’s approach draws from [Broda and Weinstein \(2006\)](#). As discussed in section 4.2, in addition to estimating elasticities at a highly disaggregated level [Broda and Weinstein \(2006\)](#) study the effects of aggregation on their estimated elasticities, and they find that both the average and median decline with aggregation. Hence, for their estimates, it is likely that an aggregate elasticity estimate would be lower than the median sectoral elasticity. We can ask what would Ossa’s aggregate elasticity need to be in order for his aggregate GFT to match his multi-sectoral GFT? Based on [Ossa \(2015\)](#), Table 2, columns 1-3 (with no adjustment for intermediate and non-traded goods), it would need to be around 1, which is a plausible number.

CP is one of the few papers that also estimates an aggregate elasticity in a model-consistent way. Their aggregate elasticity, 4.49 is about 0.5 higher than their median sectoral elasticity. The higher aggregate elasticity appears to play some role in their finding that the multi-sectoral model yields greater gains than the one-sector model. We recognize that different estimation methodologies applied to different data sets could lead to different results.

We return to the words “sectoral heterogeneity”. They can have multiple interpretations. One rationale for using the median sectoral elasticity (or a similar average of sectoral elasticities) as a proxy for the aggregate elasticity is if we interpret sectoral heterogeneity as a “mean-preserving spread”, similar to the way macroeconomists interpret a change

in risk.<sup>37</sup> Then, comparing the GFT with a median sectoral elasticity (rather than the model-consistent estimated elasticity), would reveal how the GFT are affected by a change in the “variance” of the elasticities. The comparison between the benchmark model and the “Agg1” column is consistent with this rationale. Moreover, the mean-preserving spread concept would be compatible with our first set of counterfactual exercises in which we shut down sectoral heterogeneity one model mechanism at a time. However, as we have argued, for an assessment of the importance of sectoral heterogeneity across many dimensions, we should compare a multi-sector model with model-consistent parameters against an aggregate model with model-consistent parameters.

As presented in section 4.2, in the spirit of [Broda and Weinstein \(2006\)](#), we estimated elasticities for 10 and 4 tradable sectors. We found that as the number of sectors falls, and there is more aggregation, the estimated elasticities are typically lower. The median elasticities for the 10-sector and 4-sector models are 3.8 and 3.4, respectively. We now conduct GFT calculations for both of these models and the results are indicated in columns “10sec” and “4sec” in [Table 6](#). For comparison, the benchmark model and aggregate model results are also included in columns two and five. Going from left to right, and looking at individual countries, we can see that for many of them there is not a monotonic pattern in which the GFT increase as the number of sectors (and the estimated elasticities) falls. For example, the GFT in the 10-sector model are virtually identical that of the benchmark model (which has 19 tradable sectors). Indeed, for more than half the countries, the GFT are slightly larger in the benchmark model than in the 10-sector model. Also, the GFT results for the 4-sector model are only about 0.2 percentage points higher larger than that of the 10-sector model. Finally, the GFT of the aggregate model are about 1 percentage point higher than in the 4-sector model. Overall, these results suggest that the magnitudes of the (appropriately estimated) elasticities are he most important force in the GFT, but other forces – such as input-output linkages and trade shares – do matter.

**Table 6:** Gains from Trade (percent)

Country	BM	10sec	4sec	Agg	BMSimAgg
AUS	2.11	2.02	2.08	2.78	2.52

<sup>37</sup>For example, the main framework in [Imbs and Mejean \(2015\)](#) is one in which the aggregate elasticity is a mean-preserving spread of the sectoral elasticities.

AUT	4.90	5.03	5.35	7.16	6.52
BLX	6.40	6.61	3.62	2.20	2.00
CAN	3.87	3.88	4.47	5.37	4.89
DEU	1.91	1.98	2.10	3.02	2.75
DNK	5.57	5.14	5.55	6.59	6.01
ESP	2.32	2.38	2.77	3.99	3.63
FIN	3.94	3.95	4.18	5.36	4.88
FRA	2.10	2.08	2.33	3.23	2.94
GBR	2.76	2.80	3.09	4.39	3.99
GRC	4.67	4.99	6.02	7.20	6.56
IRL	8.33	8.19	8.40	9.25	8.44
ITA	3.09	3.07	3.52	5.14	4.68
JPN	0.40	0.38	0.42	0.59	0.54
MEX	3.96	4.11	3.90	5.67	5.16
NLD	7.51	7.46	7.50	10.11	9.22
NOR	5.53	5.45	6.18	6.83	6.22
NZL	4.13	3.94	4.57	4.68	4.26
PRT	5.95	6.08	6.65	7.90	7.20
SWE	4.66	4.61	4.62	6.24	5.68
USA	1.03	1.02	1.18	1.52	1.38
Average	4.05	4.06	4.21	5.20	4.74
Median	3.96	3.95	4.18	5.36	4.88
Max	8.33	8.19	8.40	10.11	9.22
Min	0.40	0.38	0.42	0.59	0.54

BM: Benchmark model; 10sec: 10 sector model; 4sec: 4 sector model; Agg: Aggregate model; BMSimAgg: Aggregate model parameterized from simulated benchmark model

In detail, we explain the U.S. GFT results for the 10-sector vs. 4-sector model and for the 4-sector vs. aggregate model. For the first comparison, the vast majority of the gains are driven by two sectors in the 10-sector model (collectively, ISIC 383 and 384, electric machinery and transport equipment), and by one sector in the 4-sector model (collectively, ISIC 371, 381, 383, 384, hereafter “heavy manufacturing”). And it turns out the GFT contributed by these two sectors in the 10-sector model are about the same as the GFT contributed by this single sector in the 4-sector model. The trade elasticities for the two sectors in the 10-sector model are 3.27 and 4.47, and the trade elasticity for the single sector in the 4-sector model is 3.27. Based on the elasticities alone, it would be expected that the gains from trade would be larger in the 4-sector model. It turns out that the sector in the 10-sector model with the higher  $\theta^s$  (which would normally imply lower GFT), also has a large  $\widehat{D}_{nn}^s$ , and a relatively high  $\alpha_n^s$ , and low  $\gamma_n^s$ . So, these three forces offset the higher  $\theta^s$ , and lead to GFT about the same as in the 4-sector model.

For the second comparison, as mentioned above, in the 4-sector model, most of the GFT are driven by one sector (heavy manufacturing). So let us compare this sector in the 4-sector model to the aggregate model. The aggregate model has a smaller  $\widehat{D}_{nn}$ , but a higher  $\alpha_n$  than heavy manufacturing; it turns out these two forces just offset each other. The value-added gross output ratios  $\gamma_n$  are about the same. So, it boils down to the trade elasticities  $\theta$ . In the aggregate model it is 2.37, and in the heavy manufacturing sector, it is 3.27. This accounts for most of the difference. If the trade elasticity in heavy manufacturing was 2.37, then, three-fourths of the gap in the GFT would be eliminated.

To provide further evidence in support of our aggregate elasticity estimate, we conduct a Monte Carlo type exercise in which we simulate data from our benchmark multi-sector model and, then, treat that data as if it were generated from an aggregate model. We then estimate a single aggregate elasticity using the SW SMM methodology, and with that elasticity, and the other aggregate values of parameters and data, compute the GFT.

Specifically, using our estimated sectoral  $\theta^s$ 's and country-sector  $T_n^s$ 's, we simulate prices and trade shares from our multi-sectoral model by following steps 3-7 in Appendix 7.3. This generates a sample of 1410 prices (with the number of prices from each sector corresponding to the actual data), and of bilateral sectoral trade shares. We aggregate the sectoral trade shares by using the sectoral expenditure shares ( $\alpha_n^s$ ) to yield the aggregate trade share  $\frac{D_{ni}}{D_{ii}}$ .<sup>38</sup> We treat this simulated aggregate trade share and the simulated prices as the “actual” data for an aggregate world, and then follow steps 1-9 in Appendix 7.3 to estimate the aggregate  $\theta$  just as we did for the true actual data.<sup>39</sup> Our SMM estimates for aggregate  $\theta$  are in a tight range, and the median (across Monte Carlo simulations) is 2.61, which is close to our actual estimate of 2.37. The important message from this exercise is that an aggregate  $\theta$  estimate that is less than the minimum of the sectoral  $\theta^s$  estimates is a consistent model-based outcome.

With this simulated estimate of the aggregate  $\theta$ , we then conduct the GFT calculations

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<sup>38</sup>One way to understand the reason for using the sectoral expenditures shares is the following: The Monte Carlo exercise uses the estimated sector level  $T_n^s$ 's. These  $T_n^s$ 's do not capture the relative size of sectors, whereas in the aggregate theta estimation, which used an aggregate gravity equation, the estimated  $T_n$  implicitly reflects the relative size of the sectors. The relative size of the sectors needs to be captured via an adjustment, which is the expenditure share of each sector.

<sup>39</sup>Specifically, we run 10 Monte Carlo simulations. In each, we simulate 50,000 goods per tradable sector, or 950,000 goods total.

in the same way we did before. These results are given in the final column of Table 6. The GFT are about a half percentage point lower than in the aggregate model, which would be expected as our  $\theta$  estimate for the Monte Carlo exercise is close to our aggregate  $\theta$  estimate. The median GFT is close to a full percentage point higher than the median GFT in the benchmark model.

There are two lessons from our 10-sector and 4-sector aggregation exercise and from our Monte Carlo exercise. First, while the elasticity estimates may be the single most important force driving the GFT results in the benchmark vs. aggregate model, they are not the only force that matters. Second, our results are, in a sense, doubly model-consistent – a model-consistent estimate of an aggregate elasticity that is generated from a simulation of our benchmark model with model-consistent estimates of sectoral elasticities yields an elasticity that is close to our actual aggregate elasticity estimate, and GFT fairly close to the benchmark model GFT.

## 6 Conclusion

The goal of our paper is to quantitatively assess the role of sectoral heterogeneity in the gains from trade. To do so, we start from a benchmark 20-sector, 21-country Eaton-Kortum-type Ricardian trade model that draws from [Caliendo and Parro \(2015\)](#) and [Alvarez and Lucas \(2007\)](#). We estimate the sectoral trade elasticities using micro-price data and the SMM estimator developed by [Simonovska and Waugh \(2014a\)](#). Other parameters and variables are calibrated directly from the data. With the benchmark model, we compute the gains from trade (GFT) relative to autarky, and we then conduct two sets of counterfactuals. In the first set, we start from the benchmark model and shut down one or two sources of heterogeneity at a time, which we think of as “inspect the mechanism” exercises. In the second set, we compare the benchmark model against an aggregate model in which the aggregate trade elasticity is also estimated via SMM.

Our main result from both sets of counterfactuals is that increased heterogeneity does not necessarily imply increased GFT. This should be clear as a theoretical matter from the welfare gains formulas developed in CP, [Ossa \(2015\)](#), [Costinot and Rodriguez-Clare \(2014\)](#),



and other papers. It depends on how sectoral value-added shares, final demand shares, trade elasticities, input-output linkages, and domestic expenditure shares interact with each other. However, it remained a quantitative question as to whether this holds in the data. Previous research had suggested that sectoral heterogeneity does lead to significantly higher gains. Our paper shows that this is not true. Moreover, for most of the counterfactuals we run, sectoral heterogeneity only makes a small difference.

The main difference between our results and the previous research is that we use model-consistent trade elasticity estimates of both our benchmark model and our aggregate model. By contrast, much of the previous research uses an average of the sectoral elasticities as a stand-in for the aggregate elasticity. As our work, and previous research, have shown, an appropriate estimated aggregate elasticity is likely to be less than an average of sectoral elasticities. With a lower elasticity, all else equal, there will be greater GFT.

Our results suggest the following question: Can the aggregate elasticity in a framework without all the rich sectoral heterogeneity of our benchmark model be thought of as the elasticity that best captures that heterogeneity in a way to yield roughly similar GFT? This question is broadly related to the themes of [Costinot and Rodriguez-Clare \(2018\)](#) and [Adao, Costinot, and Donaldson \(2017\)](#), which develop a mapping from potentially rich and complex trade frameworks to the implicit demand for foreign factor services, in which there is just one relevant elasticity. This is one avenue for future research.

While our [Caliendo and Parro \(2015\)](#) framework permits a great deal of heterogeneity, it does not allow for heterogeneity of entry into production as in [Melitz \(2003\)](#), [Melitz and Redding \(2015\)](#), and [Simonovska and Waugh \(2014b\)](#), for example. In addition, modeling the distribution sector, as in [Giri \(2012\)](#), for example, could improve the mapping of the price data to the model counterparts. These are two additional avenues for future research.

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## 7 Appendix

### 7.1 Appendix A: Equilibrium in Relative Changes

The counterparts to (2.4),(2.8), (2.9), (2.10), and (2.11) expressed in relative terms are given below:

$$\widehat{P}_n^s = \left( \sum_{i=1}^N D_{ni}^s \left( \widehat{c}_i^s \widehat{d}_{ni}^s \right)^{-\theta^s} \right)^{\frac{-1}{\theta^s}} \quad (7.1)$$

$$\widehat{D}_{ni}^s = \left( \frac{\widehat{c}_i^s \widehat{d}_{ni}^s}{\widehat{P}_n^s} \right)^{-\theta^s} \quad (7.2)$$

$$L_n X_n^{s'} = \alpha_n^s w_n' L_n + \sum_{r=1}^S (1 - \gamma_n^r) \xi_n^{s,r} \sum_{i=1}^N L_i X_i^{r'} D_{in}^{r'} \quad (7.3)$$

$$\sum_{s=1}^S L_n X_n^{s'} = \sum_{s=1}^S \sum_{i=1}^N L_i X_i^{s'} D_{in}^{s'} \quad (7.4)$$

$$L_n w_n' l_n^s = \gamma_n^s \sum_{i=1}^N L_i X_i^{s'} D_{in}^{s'} \quad , \quad s = 1, \dots, S \quad (7.5)$$

### 7.2 Appendix B: Calibrating Parameters of Production Function

We need to calibrate two sets of parameters of the production function. First, the ratio of value-added to gross output -  $\gamma_n^s$ . Second, the use of a sector  $r$  composite good as an intermediate input to produce sector  $s$  goods -  $\xi_n^{r,s}$ .

To compute  $\gamma_n^s$  for the tradable sectors, we take the ratio of value-added to gross output. Data on value added and gross output for each sector in every country come from the World Bank TPP database for the year 1990. Missing data on the two series were replaced by data from OECD STAN database. Furthermore, for the non-traded sector, which includes all sectors except manufacturing, the value-added to gross output ratio was computed using the OECD STAN Database.

Data to construct  $\xi_n^{r,s}$  come from the 1995 national input-output tables (NIOT) of the

World Input-Output Database (WIOD), release 2013 (Timmer, Dietzenbacher, Los, Stehrer, and de Vries (2015)). The sector definition differs from that used in the TPP database, and therefore we mapped the WIOD sectors into our 19 TPP sectors. The mapping is provided in Table 7.

**Table 7:** Concordance between TPP and WIOD Sectors

TPP ISIC Code	TPP Sector Description	WIOD Sector
311	Food products	Food, Beverages and Tobacco
313,314	Beverages and Tobacco	
321	Textiles	Textiles and Textile Products
322	Wearing apparel, except footwear	
323	Leather products	Leather, Leather and Footwear
324	Footwear, except rubber or plastic	
331	Wood products, except furniture	Wood and Products of Wood and Cork
332	Furniture, except metal	
341,342	Paper and products and printing and publishing	Pulp, Paper, Paper , Printing and Publishing
352	Other chemicals	Chemicals and Chemical Products
355	Rubber products	Rubber and Plastics
356	Plastic products	
361	Pottery, china, earthenware	Other Non-Metallic Mineral
362	Glass and products	
369	Other non-metallic mineral products	
371	Iron and steel	Basic Metals and Fabricated Metal
381	Fabricated metal products	
383	Machinery, electric	Electrical and Optical Equipment
384	Transport equipment	Transport Equipment

As is evident from the table, there is greater level of disaggregation within manufacturing in the TPP data than in the WIOD input-output tables, and therefore multiple TPP sectors span a given WIOD sector. As a result, the intermediate input use coefficients (share of a “supply” sector in the total expenditure of “use” sector on intermediates) for WIOD sectors had to be split between multiple TPP sectors. Due to a lack of information, we performed an equal split across TPP sectors. For example, consider the supply WIOD sector ( $r$ ) “Food, Beverages and Tobacco” (FBT) and let’s denote its use in every use sector  $s$  by  $\gamma_n^{FBT,s}$ . Then the coefficients for the corresponding supply TPP sectors - “Food products” (F) and “Beverages and Tobacco” (BT) - are given by  $\gamma_n^{F,s} = \gamma_n^{BT,s} = \gamma_n^{FBT,s}/2$ . Furthermore, continuing with this example, the split will also imply that we will now have two identical sets of input use coefficients for the two use sectors at the TPP level - one for “Food products” (F) and the other for “Beverages and Tobacco” (BT) - instead of the single

set for “Food, Beverages and Tobacco” (FBT) at the WIOD level. Importantly, the split does not affect that fact that for a use sector  $s$   $\sum_{r=1}^{S+1} \xi_n^{r,s} = 1$ .<sup>40</sup>

Lastly, consistent with our definition of the the non-traded sector, all other WIOD sectors were aggregated into the single non-traded sector, and therefore (a) expenditure of a manufacturing sub-sector on the non-traded sector’s good is simply the sum of expenditures across all non-manufacturing WIOD sectors, and (b) expenditure of the single non-traded sector on a manufacturing sub-sector’s good is the sum of expenditures across all non-manufacturing WIOD sectors on that sub-sector’s good.

### 7.3 Appendix C: Methodology for Estimating Sector-Level $\theta$ ’s and $d_{ij}$ ’s

For two countries  $i$  and  $j$  and for sector  $s$ , recall that we use (2.8) to obtain:

$$\frac{D_{ni}^s}{D_{ii}^s} = \frac{(A^s)^{-\theta^s} \left( \frac{c_i^s d_{ni}^s}{P_n^s} \right)^{-\theta^s} \lambda_i^s}{(A^s)^{-\theta^s} \left( \frac{c_i^s d_{ii}^s}{P_i^s} \right)^{-\theta^s} \lambda_i^s} = \left( \frac{P_i^s d_{ni}^s}{P_n^s} \right)^{-\theta^s}$$

This corresponds to equation (12) in EK at the sectoral level. The log version of this expression can be estimated for each sector individually to obtain the  $\theta^s$ ’s that correspond to  $\theta$  in EK.<sup>41</sup> The log version can be written as:

$$\log \left( \frac{D_{ni}^s}{D_{ii}^s} \right) = -\theta^s \log \left( \frac{P_i^s d_{ni}^s}{P_n^s} \right) , \quad (7.6)$$

and similar to EK and SW, we use

$$\log \left( \frac{P_i^s d_{ni}^s}{P_n^s} \right) = \max_x \{r_{ni}(x^s)\} - \frac{\sum_{j=1}^{H^s} [r_{ni}(x^s)]}{H^s} ,$$

where  $r_{ni}(x^s) = \log p_n^s(x^s) - \log p_i^s(x^s)$ ,  $\max_x$  means the highest value across goods, and  $H^s$

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<sup>40</sup>We dropped three WIOD sectors due to lack of a clear mapping into the 19 TPP sectors. These WIOD sectors include - Coke, Refined Petroleum and Nuclear Fuel, Machinery, Nec, and Manufacturing, Nec; Recycling. Thus, to begin with the WIOD input use coefficients for every use sector  $s$  was normalized by the sum across the  $r$  supply sectors to ensure that  $\sum_{r=1}^{S+1} \xi_n^{r,s} = 1$  for every  $s$  at the WIOD level of disaggregation.

<sup>41</sup>if we had only one sector, we would have  $\theta = \theta^{EK}$  where  $\theta^{EK}$  represents  $\theta$  in EK

is the number of goods in sector  $s$  of which prices are observed in the data. This corresponds to equation (13) in EK.

Using (3.1), we employ two methods to estimate sector-level  $\theta$ 's: (i) method-of-moments (MM) estimator used by EK; (ii) simulated-method-of-moments (SMM) estimator used by SW. While the former is the mean of the left-hand-side variable over the mean of the right-hand-side variable in (3.1), the latter is much more detailed. The SMM estimator can be obtained as follows for each sector  $s$ :

1. Estimate  $\theta^s$  using MM estimator (as in EK) together with trade and price data in (3.1). Call this  $\theta_{EK}^s$ .

- Note: this is done for only the EU countries for which we have price data.

2. Estimate gravity equation using the specification employed in SW:

$$\frac{D_{ni}^s}{D_{nn}^s} = \frac{(A^s)^{-\theta^s} \left( \frac{c_i^s d_{ni}^s}{P_n^s} \right)^{-\theta^s} \lambda_i^s}{(A^s)^{-\theta^s} \left( \frac{c_n^s d_{nn}^s}{P_n^s} \right)^{-\theta^s} \lambda_n^s} = \left( \frac{c_i^s d_{ni}^s}{c_n^s} \right)^{-\theta^s} \frac{\lambda_i^s}{\lambda_n^s}$$

In logs, the above becomes:

$$\ln \left( \frac{D_{ni}^s}{D_{nn}^s} \right) = \ln \left( (c_i^s)^{-\theta^s} \lambda_i^s \right) - \ln \left( (c_n^s)^{-\theta^s} \lambda_n^s \right) - \theta^s \ln (d_{ni}^s)$$

and can be estimated with fixed effects as follows:

$$\ln \left( \frac{D_{ni}^s}{D_{nn}^s} \right) = T_i^s - T_n^s - \theta^s \ln (d_{ni}^s) \quad , \quad (7.7)$$

where

$$T_i^s = \ln \left( (c_i^s)^{-\theta^s} \lambda_i^s \right)$$

and

$$T_n^s = \ln \left( (c_n^s)^{-\theta^s} \lambda_n^s \right)$$

and

$$\ln d_{ni}^s = \underbrace{dist_I}_{\text{distance}} + \underbrace{brdr}_{\text{border}} + \underbrace{lang}_{\text{language}} + \underbrace{tblk_G}_{\text{trade block}} + \underbrace{src_i^s}_{\text{source effect}} + \varepsilon_{ni}^s .$$

where  $dist_I$  ( $I = 1, \dots, 6$ ) is the effect of distance between  $n$  and  $i$  lying in the  $I$ th interval,  $brdr$  is the effect of  $n$  and  $i$  sharing a border,  $lang$  is the effect of  $n$  and  $i$  sharing a language,  $tblk_G$  ( $G = 1, 2$ ) is the effect of  $i$  and  $j$  belonging to a free trade area  $G$ , and  $src_i^s$  ( $i = 1, \dots, N$ ) is a source effect. The error term  $\varepsilon_{ni}^s$  captures trade barriers due to all other factors, and is assumed to be orthogonal to the regressors. The errors are assumed to be normally distributed with mean zero and variance,  $\sigma_\varepsilon$ . The six distance intervals (in miles) are:  $[0, 375)$ ;  $[375, 750)$ ;  $[750, 1500)$ ;  $[1500, 3000)$ ;  $[3000, 6000)$  and  $[6000, \text{maximum}]$ . The two free trade areas are the European Union (EU) and the North-American Free Trade Agreement (NAFTA).  $T_i^s$  is captured as the coefficient on source-country dummies for each sector  $s$ .

Because there are zero-trade observations in trade data, we use Poisson pseudo maximum likelihood (PPML) estimation as advocated in Silva-Tenreyo (2006).

3. SW show that the inverse of the marginal cost of production in sector  $s$  of country  $n$ , which is given by:

$$u_n^s = \frac{z_n^s(x^s)}{c_n^s}$$

is distributed according to:

$$M_n^s(u_n^s) = \exp\left(-(\exp(T_n^s))(u_n^s)^{-\theta^s}\right)$$

where  $T_n^s = \ln\left((c_n^s)^{-\theta^s} \lambda_n^s\right)$  is the country-fixed effect estimated above.

- This can also be done by using the “inverse transform method”. The idea is that probability draws from the Fréchet( $\exp(T_n^s), \theta^s$ ) can be transformed into random draws from a standard uniform distribution. If  $m$  has a standard uniform distribution, then the inverse of the marginal cost is given by

$$\left(\frac{\log(m)}{-\exp(T_n^s)}\right)^{-\frac{1}{\theta^s}} .$$



We adopt this method in the code. This is in line with SW.

4. Therefore, for a given  $\theta^s$ , say,  $\theta_G^s$ , we can use the estimated gravity equation's source dummies ( $T_n^s$ 's) to estimate source marginal costs, and the coefficients on the trade cost measures to estimate bilateral trade costs ( $d_{ij}^s$ ).

5. Using the inverse of the marginal costs, and the trade costs, we compute, for each good, the set of all possible destination prices. Then, select the minimum price for each destination:

$$p_n^s(x^s) = \min_i \left\{ \frac{c_i^s d_{ni}^s}{z_i^s} \right\}$$

This is the simulated equilibrium price for one good. We allow for 50,000 possible goods in each sector. These simulated prices represent the pool of prices that samples will be drawn from.

6. Given the simulated equilibrium prices,  $p_n^s(x^s)$ , the price  $P_n^s$  of the sector-level consumption index  $C_n^s$  can be simulated as follows:

$$P_n^s = \left[ \int_0^1 p_n^s(x^s)^{1-\sigma} dx^s \right]^{\frac{1}{1-\sigma}},$$

where we use  $\sigma = 2$  following SW. The expenditure of country  $n$  on good  $x$  imported from country  $i$  is given by:

$$p_n^s(x^s) q_n^s(x^s) = \left( \frac{p_n^s(x^s)}{P_n^s} \right)^{1-\sigma} X_n^s,$$

where  $X_n^s$  is the total expenditure by country  $n$  on sector  $s$  goods, i.e.,  $X_n^s = P_n^s C_n^s$ . Adding this expenditure across all goods imported by  $n$  from  $i$ , and then dividing both sides by  $X_n^s$  gives us the simulated trade share:

$$\widehat{D}_{ni}^s = \frac{X_{ni}^s}{X_n^s} = \int_{\Omega_{ni}} \left( \frac{p_n^s(x^s)}{P_n^s} \right)^{1-\sigma} dx^s,$$

where  $\Omega_{ni}$  is the set of goods imported by country  $n$  from country  $i$ .

7. We want to include an error term into these simulated trade shares. To do so, we conduct the following steps:

- (a) Calculate the trade shares normalized by the importing country's own trade share, i.e.,  $\widehat{D}_{ni}^s / \widehat{D}_{nn}^s$ .
- (b) Take the logarithm of these normalized trade shares and add the residuals from the gravity equation (with replacement in each simulation). This gives us the log normalized trade shares with errors. Denote these by  $\log(D_{ni}^s / D_{nn}^s)$ .
- (c) Take the exponential of this to get  $D_{ni}^s / D_{nn}^s$ . These are the normalized simulated equilibrium trade shares.
- (d) Finally, we unwind these normalized trade shares into levels to get  $D_{ni}^s$ . To do that, we use that fact that for an importing country  $n$ , the sum of its trade shares across all suppliers  $i = 1, \dots, N$  is one, i.e.,  $\sum_{i=1}^N D_{ni} = 1$ . So, it is implied that  $\sum_{i=1}^N (D_{ni}^s / D_{nn}^s) = 1 / D_{nn}^s$ . Accordingly, we divide the normalized trade shares  $D_{ni}^s / D_{nn}^s$  by  $1 / D_{nn}^s$ , and that gives us the level trade share  $D_{ni}^s$  which, importantly, incorporates the residuals from the gravity equation.

8. Using the simulated trade (incorporating the residuals) shares and the simulated prices, draw goods prices – the actual number equals the number of goods in our sample (in the sector) – and trade shares from the pool of simulated prices and trade shares. Estimate  $\theta^s$  using the MM estimator (as in EK) according to:

$$\underbrace{\log\left(\frac{D_{ni}^s}{D_{ii}^s}\right)}_{\text{Simulated Trade Data}} = -\theta_S^s \underbrace{\log\left(\frac{P_i^s d_{ni}^s}{P_n^s}\right)}_{\text{Simulated Price Data}}$$

which we call  $\theta_S^s$ . We repeat this exercise 1,000 times.

- This is done for only the EU countries for which we have price data.

9. Within 1,000 simulated  $\theta_S^s$ 's, we search for  $\theta_G^s$ , that minimizes the weighted distance

between  $\theta_{EK}^s$  and the average  $\theta_G^s$ :

$$\theta_{SMM}^s = \arg \min_{\theta_G^s} \left[ \left( \theta_{EK}^s - \frac{1}{1000} \sum_{s=1}^{1000} \theta_S^s \right) \mathbf{W} \left( \theta_{EK}^s - \frac{1}{1000} \sum_{s=1}^{1000} \theta_S^s \right) \right]$$

where  $W$  is the continuously updated weighting matrix defined as:

$$\mathbf{W} = \frac{1}{1000} \sum_{s=1}^{1000} \theta_S^s \left[ \left( \theta_{EK}^s - \frac{1}{1000} \sum_{s=1}^{1000} \theta_S^s \right) \left( \theta_{EK}^s - \frac{1}{1000} \sum_{s=1}^{1000} \theta_S^s \right) \right]$$

We also used alternative  $W$  definitions such as (i) the one used by [Eaton, Kortum, and Kramarz \(2011\)](#) based on bootstrapping, (ii) an alternative version of  $W$  above which is

$$\mathbf{W}_A = \frac{1}{1000} \sum_{s=1}^{1000} \theta_S^s \left[ \begin{array}{c} \left( \left( \theta_{EK}^s - \frac{1}{1000} \sum_{s=1}^{1000} \theta_S^s \right) - \frac{1}{1000} \sum_{s=1}^{1000} \left( \theta_{EK}^s - \frac{1}{1000} \sum_{s=1}^{1000} \theta_S^s \right) \right) \\ \times \left( \left( \theta_{EK}^s - \frac{1}{1000} \sum_{s=1}^{1000} \theta_S^s \right) - \frac{1}{1000} \sum_{s=1}^{1000} \left( \theta_{EK}^s - \frac{1}{1000} \sum_{s=1}^{1000} \theta_S^s \right) \right) \end{array} \right]$$

and (iii) the identity matrix; however, the results were very close to each other. Currently, we are using the benchmark  $W$  defined above. The selected  $\theta_G^s$  is the SMM estimate of  $\theta^s$ , which we denote by  $\theta_{SMM}^s$ .

Following [Eaton, Kortum, and Kramarz \(2011\)](#) and SW, we calculate standard errors using a bootstrap technique, taking into account both sampling error in the trade shares and simulation error. In addition, owing to the fact that some sectors have a small number of prices (an issue that the other two papers did not face, as they estimated only an aggregate elasticity), we have added sampling error in the price data. That is, we are treating the prices as a sample, not a population. This adds an extra step to the bootstrapped methodology. In particular, we proceed as follows:

1. Assume that the error terms in equation of (7.6) have a log normal distribution. Draw error terms from that distribution and add them to the fitted values of equation (7.6). This will generate a new set of data for the left hand side of equation (7.6).
2. Following Steps 2-5 of SMM estimation above, randomly draw goods prices to generate

a new set of prices using  $\theta_{SMM}^s$ , where the number of draws matches the actual number of goods in the price data. This will generate a new set of data for the right hand side of equation (7.6).

3. For each re-sampling  $b$ , with the newly generated data set, estimate  $\theta_{b,SMM}^s$  by following all 9 steps for SMM estimation above.
4. Repeat this exercise 25 times and compute the estimated standard error of the estimate of  $\theta_{SMM}^s$  as follows:

$$S.E. (\theta_{SMM}^s) = \left[ \frac{1}{25} \sum_{b=1}^{25} (\theta_{b,SMM}^s - \theta_{SMM}^s)' (\theta_{b,SMM}^s - \theta_{SMM}^s) \right]^{\frac{1}{2}}$$

where  $\theta_{b,SMM}^s$  is a vector with the size of  $(25 \times 1)$ .

## 7.4 Appendix D: Comparison of EK estimator across one-sector and multi-sector models

EK estimator at the sectoral level uses the following expression:

$$\log \left( \frac{D_{ni}^s}{D_{ii}^s} \right) = -\theta^s \log \left( \frac{P_i^s d_{ni}^s}{P_n^s} \right) \quad (7.8)$$

where

$$\log \left( \frac{P_i^s d_{ni}^s}{P_n^s} \right) = \max_x \{r_{ni}(x^s)\} - \frac{\sum_{x=1}^{H^s} [r_{ni}(x^s)]}{H^s} \quad (7.9)$$

Similarly, EK estimator at the aggregate level uses:

$$\log \left( \frac{D_{ni}}{D_{ii}} \right) = -\theta \log \left( \frac{P_i d_{ni}}{P_n} \right) \quad (7.10)$$

where

$$\log \left( \frac{P_i d_{ni}}{P_n} \right) = \max_x \{r_{ni}(x)\} - \frac{\sum_{x=1}^H [r_{ni}(x)]}{H} \quad (7.11)$$

In order to make a comparison between the one-sector  $\theta$  and multi-sector  $\theta^s$ 's, for

simplicity, assume that:

$$\underbrace{\log\left(\frac{D_{ni}^s}{D_{ii}^s}\right)}_{\text{Multi-Sector}} = \underbrace{\log\left(\frac{D_{ni}}{D_{ii}}\right)}_{\text{One-Sector}} \quad \text{for all } s \quad (7.12)$$

and

$$\underbrace{\frac{\sum_{x=1}^{H^s} [r_{ni}(x^s)]}{H^s}}_{\text{Multi-Sector}} = \underbrace{\frac{\sum_{x=1}^H [r_{ni}(x)]}{H}}_{\text{One-Sector}} = 0 \quad \text{for all } s \quad (7.13)$$

which implies that comparison of estimates reduces to the following comparison of right-hand-sides:

$$\underbrace{\log\left(\frac{P_i^s d_{ni}^s}{P_n^s}\right)}_{\text{Multi-Sector}} = \max_x \{r_{ni}(x^s)\} \quad \text{versus} \quad \underbrace{\log\left(\frac{P_i d_{ni}}{P_n}\right)}_{\text{One-Sector}} = \max_x \{r_{ni}(x)\}$$

where, due to using the max operator, we can write:

$$\max_x \{r_{ni}(x)\} = \max_s \left\{ \max_x \{r_{ni}(x^s)\} \right\}$$

Hence, for each country pair  $n, i$ , the maximum price difference for the one-sector model is the maximum (across sectors) of the sector-specific maximum price differences.

Within this picture (i.e., when equations 7.12 and 7.13 hold), assume that sector  $L$  has the lowest sector-level  $\theta^s$  estimate (compared to other sectors). Now, consider two cases:

1. **Case #1:** Assume that for all country pairs, sector  $L$  has the maximum price differ-

ence. Hence, in technical terms, for all  $n, i$ , we have:

$$\begin{aligned}
\max_x \{r_{12}(x)\} &= \max_s \left\{ \max_x \{r_{12}(x^s)\} \right\} = \max_x \{r_{12}(x^L)\} \\
\max_x \{r_{13}(x)\} &= \max_s \left\{ \max_x \{r_{13}(x^s)\} \right\} = \max_x \{r_{13}(x^L)\} \\
&\cdot \\
&\cdot \\
&\cdot \\
\max_x \{r_{ni}(x)\} &= \max_s \left\{ \max_x \{r_{ni}(x^s)\} \right\} = \max_x \{r_{ni}(x^L)\}
\end{aligned}$$

In this case, because the average across country pairs is used for the (RHS of) MM estimator, we have the following:

$$\underbrace{\theta^L}_{\text{Multi-Sector}} = \underbrace{\theta}_{\text{One-Sector}}$$

which means that one-sector  $\theta$  equals the lowest  $\theta^s$  across sectors.

2. **Case #2:** At least for one country pair (say, 1, 2), a sector other than  $L$  (call this other sector  $M$ ) has the maximum price difference. In technical terms, we have:

$$\begin{aligned}
\max_x \{r_{12}(x)\} &= \max_s \left\{ \max_x \{r_{12}(x^s)\} \right\} = \max_x \{r_{12}(x^M)\} > \max_x \{r_{12}(x^L)\} \\
\max_x \{r_{13}(x)\} &= \max_s \left\{ \max_x \{r_{13}(x^s)\} \right\} = \max_x \{r_{13}(x^L)\} \\
&\cdot \\
&\cdot \\
&\cdot \\
\max_x \{r_{ni}(x)\} &= \max_s \left\{ \max_x \{r_{ni}(x^s)\} \right\} = \max_x \{r_{ni}(x^L)\}
\end{aligned}$$

In this case, because the average across country pairs is used for the (RHS of) MM estimator, we have the following:

$$\underbrace{\theta^L}_{\text{Multi-Sector}} > \underbrace{\theta}_{\text{One-Sector}}$$

since  $\max_x \{r_{12}(x^M)\} > \max_x \{r_{12}(x^L)\}$  in the first line above.

Hence, theoretically, when equations 7.12 and 7.13 hold, we have:

$$\underbrace{\theta^L}_{\text{Multi-Sector}} \geq \underbrace{\theta}_{\text{One-Sector}}$$

Our data suggest that Case #2 (introduced above) holds empirically, and equations 7.12 and 7.13 hold approximately. Hence, empirically, we have:

$$\underbrace{\theta^L}_{\text{Multi-Sector}} > \underbrace{\theta}_{\text{One-Sector}}$$

## 7.5 Appendix E: Counterfactuals Removing Two Sources of Heterogeneity

**Table 8:** Gains from Trade

Country	BM	BM8	BM9	BM10	BM11	BM12	BM13
AUS	2.11%	1.70%	1.58%	1.52%	1.94%	1.91%	1.77%
AUT	4.90%	4.39%	4.16%	3.92%	4.68%	4.67%	4.53%
BLX	6.40%	1.34%	1.22%	1.16%	6.14%	6.27%	5.87%
CAN	3.87%	3.33%	2.95%	2.91%	3.04%	3.52%	2.88%
DEU	1.91%	1.82%	1.70%	1.63%	1.78%	1.85%	1.78%
DNK	5.57%	4.30%	3.79%	3.56%	6.30%	5.94%	6.35%
ESP	2.32%	2.42%	2.24%	2.14%	2.09%	2.16%	1.96%
FIN	3.94%	3.45%	3.05%	2.81%	4.13%	3.77%	3.69%
FRA	2.10%	1.97%	1.81%	1.75%	1.90%	1.95%	1.80%
GBR	2.76%	2.74%	2.54%	2.37%	2.56%	2.48%	2.35%
GRC	4.67%	4.56%	4.64%	4.39%	4.30%	4.16%	4.64%
IRL	8.33%	6.19%	5.56%	5.06%	8.83%	8.32%	8.51%
ITA	3.09%	3.10%	2.93%	2.78%	2.74%	2.82%	2.53%
JPN	0.40%	0.34%	0.31%	0.31%	0.39%	0.35%	0.35%
MEX	3.96%	3.42%	3.20%	3.03%	3.73%	3.37%	3.32%
NLD	7.51%	6.54%	6.04%	5.66%	7.52%	7.17%	7.14%
NOR	5.53%	4.25%	3.74%	3.54%	6.37%	5.63%	6.31%
NZL	4.13%	2.89%	2.72%	2.61%	3.61%	3.92%	3.55%
PRT	5.95%	4.89%	4.63%	4.40%	4.71%	5.68%	4.66%
SWE	4.66%	3.90%	3.50%	3.30%	5.20%	4.36%	4.95%
USA	1.03%	0.95%	0.86%	0.82%	0.86%	0.95%	0.83%
Average	4.05%	3.26%	3.01%	2.84%	3.94%	3.87%	3.80%
Median	3.96%	3.33%	2.95%	2.81%	3.73%	3.77%	3.55%
Max	8.33%	6.54%	6.04%	5.66%	8.83%	8.32%	8.51%
Min	0.40%	0.34%	0.31%	0.31%	0.39%	0.35%	0.35%

BM: Benchmark model; BM8: benchmark model with same  $D_{ni}^s$  and  $\gamma_n^s$  across tradable sectors; BM9: benchmark model with same  $D_{ni}^s$  and  $\alpha_n^s$  across tradable sectors; BM10: benchmark model with same  $D_{ni}^s$ , and median sectoral  $\theta^s$ , across tradable sectors; BM11: benchmark model with same  $\gamma_n^s$  and  $\alpha_n^s$  across tradable sectors; BM12: benchmark model with same  $\gamma_n^s$ , and median sectoral  $\theta^s$ , across tradable sectors; BM13: benchmark model with same  $\alpha_n^s$ , and median sectoral  $\theta^s$ , across tradable sectors

## 7.6 Appendix F: Other

**Table 9:** List of Sectors: ISIC Revision 2 and Tradable Sectoral Aggregation

ISIC Code	Sector Description	10-sector	4-sector
311	Food products	1	1
313,314	Beverages and Tobacco	1	1
321	Textiles	2	2
322	Wearing apparel, except footwear	2	2
323	Leather products	3	2
324	Footwear, except rubber or plast	3	2
331	Wood products, except furniture	4	2
332	Furniture, except metal	4	2
341,342	Paper and products and printing and publishing	5	2
352	Other chemicals	6	3
355	Rubber products	6	3
356	Plastic products	6	3
361	Pottery, china, earthenware	7	3
362	Glass and products	7	3
369	Other non-metallic mineral products	7	3
371	Iron and steel	8	4
381	Fabricated metal products	8	4
383	Machinery, electric	9	4
384	Transport equipment	10	4
400	Non-traded sector		