Online Appendix to “The Missing Food Problem: Trade, Agriculture, and International Income Differences”

Trevor Tombe, University of Calgary

Contents

1 Proof of Propositions 2

2 Data and Sample of Countries 5

2.1 Data Sources and Construction 5
2.2 Labor Productivity Estimates 6
2.3 The Main Sample for Quantitative Analysis 7
2.4 Key Empirical Patterns for All Possible Countries 10
  2.4.1 Labour Productivity 10
  2.4.2 International Trade Patterns 11
  2.4.3 Trade Costs 12

3 Calibration Details 14

3.1 Production Function Parameters 15
3.2 Estimating Productivity Dispersion θ 18
3.3 Trade Cost Asymmetries 21

4 Alternative Model Specifications 24

4.1 Eliminating Initial Zeros from the Trade Matrix 24
4.2 Unbalanced Trade 26
4.3 Tariff Revenue 28

1 Proof of Propositions

Proposition 1 *If sectoral expenditures X_n^j and revenues R_n^j solve equations 4 and 5, households spend all of their income, and total income equals total value added, then $S_n^a = -S_n^m$ and*

$$X_n^a + X_n^m = \sum_{i=1}^{N} \pi_{in}^a X_i^a + \sum_{i=1}^{N} \pi_{in}^m X_i^m,$$

must hold for all n. That is, aggregate trade balances for all countries.

Proof: Summing equation 4 across all sectors in each country yields

$$\begin{aligned}\sum_{j\in\{a,m,s\}} X_n^j &= I_n + \sum_{j\in\{a,m,s\}} \sum_{k\in\{a,m,s\}} (1-\phi^k)\gamma^{kj} R_n^k, \\ &= I_n + \sum_{k\in\{a,m,s\}} (1-\phi^k) R_n^k \sum_{j\in\{a,m,s\}} \gamma^{kj}, \\ &= \sum_{k\in\{a,m,s\}} R_n^k.\end{aligned}$$

The third line follows from $\sum_{j\in\{a,m,s\}} \gamma^{kj} = 1$ and $\sum_{j\in\{a,m,s\}} \phi^j R_n^j = I_n$. Services are not tradable, so $R_n^s = X_n^s$ and therefore $X_n^a + X_n^m = R_n^a + R_n^m$. From equation 3, $R_n^j = X_n^j + S_n^j$ for $j \in \{m, a\}$, and therefore $S_n^a = -S_n^m$ must hold. The final trade balance condition immediately follows from equation 5; specifically, $R_n^j = \sum_{i=1}^N \pi_{in}^j X_i^j$. ■

Proposition 2 *The change in real GDP is*

$$\hat{Y}_n = \sum_{j\in\{a,m,s\}} \frac{\hat{w}_n^j}{\hat{P}_n^j} \hat{l}_n^j \omega_n^j, \tag{1}$$

where the weights $\omega_n^j = \phi^j R_n^j / \sum_{k\in\{a,m,s\}} \phi^k R_n^k$ are the initial GDP shares and changes in sectoral real wages (and therefore sectoral labor productivity) are

$$\frac{\hat{w}_n^j}{\hat{P}_n^j} = \left(\hat{\pi}_{nn}^j\right)^{-\frac{1}{\theta^j \phi^j}} \hat{\lambda}_n^{\beta-1} \left[\prod_{k\in\{a,m,s\}} \left(\hat{P}_n^k\right)^{\gamma^{jk}} / \hat{P}_n^j\right]^{-\frac{1-\phi^j}{\phi^j}}. \tag{2}$$

Proof: Real GDP in the counterfactual equilibrium values output using the initial prices,

$$\begin{aligned} Y_n' &= \sum_{j\in\{a,m,s\}} \frac{\phi^j \, R_n^{j\,\prime}}{P_n^{j\,\prime}} P_n^j, \\ &= \sum_{j\in\{a,m,s\}} \frac{\phi^j \, R_n^{j\,\prime}}{\hat{P}_n^j}, \\ &= \sum_{j\in\{a,m,s\}} \frac{\hat{R}_n^j}{\hat{P}_n^j} \phi^j R_n^j. \end{aligned}$$

Dividing both sides by the initial GDP $Y_n = \sum_{k\in\{a,m,s\}} \phi^k R_n^k$ yields

$$\begin{aligned} \hat{Y}_n &= \sum_{j\in\{a,m,s\}} \frac{\hat{R}_n^j}{\hat{P}_n^j} \omega_n^j, \\ &= \sum_{j\in\{a,m,s\}} \frac{\hat{w}_n^j}{\hat{P}_n^j} \hat{l}_n^j \omega_n^j \end{aligned}$$

where the second line follows from $\hat{R}_n^j / \hat{P}_n^j = \hat{w}_n^j \hat{l}_n^j / \hat{P}_n^j$ and the weights are the initial GDP shares, $\omega_n^j = \phi^j R_n^j / \sum_{k\in\{a,m,s\}} \phi^k R_n^k$. This gives the first result.

Next, the change in real wages in each sector is simple to derive. Relative changes in trade shares are

$$\hat{\pi}_{ni}^j = \left(\hat{\tau}_{ni}^j \hat{c}_i^j / \hat{P}_n^j \right)^{-\theta^j},$$

and therefore

$$\begin{aligned} \hat{\pi}_{nn}^j &= \left[\left[\left(\hat{w}_n^j \right)^{\beta} \hat{r}_n^{1-\beta} \right]^{\phi^j} \left[\prod_{k\in\{a,m,s\}} \left(\hat{P}_n^k \right)^{\gamma^{jk}} \right]^{1-\phi^j} / \hat{P}_n^j \right]^{-\theta^j}, \\ \Rightarrow \left(\hat{\pi}_{nn}^j \right)^{-\frac{1}{\theta^j \phi^j}} &= \hat{w}_n^j \hat{\lambda}_n^{1-\beta} \left[\prod_{k\in\{a,m,s\}} \left(\hat{P}_n^k \right)^{\gamma^{jk}} \right]^{\frac{1-\phi^j}{\phi^j}} / \left(\hat{P}_n^j \right)^{\frac{1}{\phi^j}} \end{aligned}$$

$$\begin{aligned}
\Rightarrow \frac{\hat{w}_n^j}{\hat{P}_n^j} &= \left(\hat{\pi}_{nn}^j\right)^{-\frac{1}{\theta^j\phi^j}} \hat{\lambda}_n^{\beta-1} \left[\prod_{k\in\{a,m,s\}} \left(\hat{P}_n^k\right)^{\gamma^{jk}}\right]^{-\frac{1-\phi^j}{\phi^j}} \left(\hat{P}_n^j\right)^{\frac{1-\phi^j}{\phi^j}}, \\
&= \left(\hat{\pi}_{nn}^j\right)^{-\frac{1}{\theta^j\phi^j}} \hat{\lambda}_n^{\beta-1} \left[\prod_{k\in\{a,m,s\}} \left(\hat{P}_n^k\right)^{\gamma^{jk}} / \hat{P}_n^j\right]^{-\frac{1-\phi^j}{\phi^j}},
\end{aligned}$$

which is the same expression as in Caliendo and Parro (2012) except for $\hat{\lambda}_n$.■

Proposition 3 *The change in welfare $\hat{U}_n$ can be decomposed into*

$$\hat{U}_n = \underbrace{\hat{w}_n\hat{P}_n^{-1}}_{\substack{\textit{Real}\\\textit{Wages}}} \cdot \underbrace{\hat{\lambda}_n}_{\substack{\textit{Labor}\\\textit{Market}}} \cdot \underbrace{\hat{\Gamma}_n}_{\substack{\textit{Subsistence}\\\textit{Food}}}$$

where $\hat{w}_n\hat{P}_n^{-1}$ captures standard real-wage effects, $\hat{\lambda}_n$ captures changes in labor allocations and distortions, and $\hat{\Gamma}_n$ captures non-homothetic preference effects.

Proof: To get welfare changes, determine changes in consumption in excess of subsistence requirements. For agriculture, define $\tilde{C}_n^a = C_n^a - \bar{a}$ for agriculture and $\tilde{C}_n^j = C_n^j$ for manufacturing and services. The household's optimal consumption choices imply $\tilde{C}_n^j = (I_n - \bar{a}P_n^a)/P_n^j$. Taking ratios,

$$\hat{\tilde{C}}_n^j = \frac{I_n' - \bar{a}\,P_n^{a\,\prime}}{(I_n - \bar{a}P_n^a)} \frac{1}{\hat{P}_n^j},$$

which can be simplified using $I_n' - \bar{a}\,P_n^{a\,\prime} = I_n\left(\hat{I}_n - \left(\frac{s_n^a-\varepsilon^a}{1-\varepsilon^a}\right)\hat{P}_n^a\right)$ and $I_n - \bar{a}P_n^a = \left(\frac{1-s_n^a}{1-\varepsilon^a}\right) I_n$ to

$$\begin{aligned}
\hat{\tilde{C}}_n^j &= \left(\frac{1-\varepsilon^a}{1-s_n^a}\hat{I}_n - \left(\frac{s_n^a-\varepsilon^a}{1-s_n^a}\right)\hat{P}_n^a\right)\frac{1}{\hat{P}_n^j}, \\
&= \frac{\hat{I}_n}{\hat{P}_n^j}\frac{1-\varepsilon^a}{1-s_n^a}\left(1 - \left(\frac{s_n^a-\varepsilon^a}{1-\varepsilon^a}\right)\frac{\hat{P}_n^a}{\hat{I}_n}\right), \\
&\equiv \frac{\hat{I}_n}{\hat{P}_n^a}\hat{\Gamma}_n,
\end{aligned}$$

where $\hat{\Gamma}_n = \frac{1-\varepsilon^a}{1-s_n^a}\left(1-\left(\frac{s_n^a-\varepsilon^a}{1-\varepsilon^a}\right)\frac{\hat{P}_n^a}{\hat{I}_n}\right)$.

As the change in overall welfare is $\hat{U}_n = \left(\hat{\tilde{C}}_n^a\right)^{\varepsilon^a}\left(\hat{C}_n^m\right)^{\varepsilon^m}\left(\hat{C}_n^s\right)^{\varepsilon^s}$, inserting the above change in above-subsistence consumption change yields $\hat{U}_n = \hat{I}_n\hat{\Gamma}_n/\hat{P}_n$, where the change in prices are $\hat{P}_n = \left(\hat{P}_n^a\right)^{\varepsilon^a}\left(\hat{P}_n^m\right)^{\varepsilon^m}\left(\hat{P}_n^s\right)^{\varepsilon^s}$.■

2 Data and Sample of Countries

In this section, I list the main sources of data and details behind how certain variables were constructed. All data sources are publicly available, though the recent UN-IDO data is not free.

2.1 Data Sources and Construction

The key variables are as follows:

Trade Flows – Trade flow data is from the BACI product-level trade database (Gaulier and Zignago, 2010), which classifies trade by harmonized system (HS) codes (2002 version). I aggregate products with two-digit HS codes 01-15 into agriculture and products with codes 16-24 or 28-97 into manufacturing. Notice this excludes mineral products and services and treats food preparations as manufactured goods.

Tariffs – The UN-TRAINS database provides a wealth of tariff data. I use trade-weighted MFN tariffs for 2005, or the closest year (older breaking ties) within 2004 or 2006. Products included in agriculture and manufacturing correspond to the HS codes listed above for trade flows.

Gross Output – The UN-IDO provides gross output and value-added in manufacturing for a large number of countries. For agriculture, gross output is available from the FAO and OECD. Data are available from the FAO using a number of measures. As trade data is in current US dollars, I use production data for 2005 valued in current US dollars. When agricultural output data is available from the OECD, I use this instead of the FAO data. There are 30 countries for which this data is available. The manufacturing, 64 countries have gross output data from the UN-IDO. For the remaining 26, I infer output from value-added data according to the average value-added to gross-output ratio for the countries in the UN-IDO data.

Agricultural Employment – Agricultural employment data are mainly from the FAO, though I augment it with data from the WDI or the CIA World Factbook as needed. The specific adjustments are occasionally necessary. In cases where FAO employment data results in implausible productivity values, I use the WDI employment data. Specifically, WDI employment is used for Armenia, Bhutan, Bulgaria, Burkina Faso, China, Kyrgyzstan, Macedonia, Moldova, Rwanda, and Slovenia. Data from the CIA World Factbook are used when WDI values are unavailable. I use this data for Bosnia and Herzegovina, Nepal, and Nigeria. Agriculture's labor share for all 90 countries used in the main quantitative exercise is reported later in this appendix.

Agricultural Consumption Share – The World Bank International Comparison Program (ICP, version 2005) provides a list in their Final Report of the share of consumption expenditures allocated to food. I use this as s_n^a to solve the initial equilibrium of the model.

Labor market distortion – The labor market distortion for each country is inferred from agriculture's share of employment and GDP. I described the employment data in the section for Labor Productivity Estimates. Agriculture's share of nominal GDP is readily available from the World Bank's WDI data. For three countries (Greece, Israel, and Qatar) the WDI share is unavailable and I use agriculture's GDP share reported in the CIA World Factbook.

2.2 Labor Productivity Estimates

To compare productivity across countries one requires value-added per worker adjusted for price differences. I construct real labor productivity for agriculture and non-agriculture for a large set of countries following Caselli (2005) and Restuccia et al. (2008).

The UN Food and Agricultural Organization's FAOSTAT reports agricultural net output at international prices for 2005. Fortunately, these data use producer prices that exclude distribution costs, which vary systematically with a country's level of development (Adamopoulos, 2011). Unfortunately, value-added in international prices is not available; so, assume it is 50% of output (consistent with evidence documented in appendix section 3.1).[1]

Non-agricultural value-added is aggregate value-added (from the Penn World Table 8.0) less agricultural value-added. A complication results from differences in how the PWT and the FAO normalize international prices (relative prices equal but overall levels differ). Following Caselli (2005), I rescale agricultural value-added uniformly across countries such that agriculture's share of GDP in the US matches the share reported in the World Development Indicators (WDI).

Finally, employment in each sector is needed to construct value-added per worker. I describe the sources for this data in the next section. With these employment data, I simply take the ratio of value-added in agriculture to the number of agricultural workers. Similarly for non-agriculture. The results of this exercises are reported in the main paper for as many countries for which sufficient data exists, not just the 90 countries used in the main quantitative exercises.

2.3 The Main Sample for Quantitative Analysis

The main quantitative analysis uses a set of 90 countries for which data exists for aggregate GDP and employment, agricultural employment and expenditure shares, and trade flows, tariff rates, and production by sector. Overall, the sample of 90 countries I work with include all major countries around the world and span a wide range of levels of development. Combined, these 90 countries account for roughly 90% of global GDP, population, and employment. I list each country in the sample, along with key data, in the Table 1.

---

[1] Restuccia et al. (2008) exploit internationally priced value-added for 1985 from Rao (1993). The correlation between our measures are 0.87 for agriculture and 0.82 for non-agriculture.

Table 1: Selected Data and Estimates for 90 Country Sample

Country	GDP per Worker (US=1)	Home Trade Shares		Ag. Labor Share	Food Budget Share	Labor Distortion
		Ag.	Nonag.			
Albania	0.21	0.84	0.12	0.45	0.21	0.36
Argentina	0.31	0.96	0.84	0.08	0.15	1.33
Armenia	0.14	0.81	0.00	0.46	0.52	0.31
Australia	0.83	0.85	0.67	0.04	0.06	0.77
Austria	0.81	0.63	0.33	0.04	0.06	0.38
Azerbaijan	0.11	0.80	0.33	0.25	0.29	0.33
Bangladesh	0.04	0.85	0.70	0.50	0.39	0.25
Bhutan	0.13	0.87	0.03	0.44	0.18	0.39
Bolivia	0.10	0.91	0.59	0.42	0.21	0.23
Bosnia	0.36	0.66	0.23	0.21	0.30	0.46
Brazil	0.18	0.95	0.87	0.13	0.10	0.40
Bulgaria	0.24	0.75	0.40	0.09	0.16	0.95
Burkina Faso	0.02	0.92	0.65	0.85	0.32	0.11
Cameroon	0.05	0.92	0.83	0.54	0.32	0.21
Canada	0.81	0.77	0.47	0.02	0.05	0.92
China	0.10	0.96	0.82	0.45	0.10	0.17
Colombia	0.18	0.87	0.66	0.17	0.17	0.45
Congo	0.08	0.73	0.07	0.36	0.12	0.08
Côte d’Ivoire	0.04	0.84	0.61	0.43	0.31	0.39
Croatia	0.47	0.63	0.55	0.06	0.16	0.82
Cyprus	0.60	0.54	0.20	0.07	0.12	0.39
Czech Republic	0.48	0.74	0.40	0.07	0.08	0.38
Ecuador	0.17	0.80	0.56	0.21	0.18	0.42
Egypt	0.15	0.82	0.55	0.28	0.33	0.44
Ethiopia	0.01	0.91	0.26	0.80	0.45	0.22
Fiji	0.11	0.65	0.31	0.38	0.22	0.27
Finland	0.77	0.86	0.57	0.04	0.06	0.61
France	0.80	0.77	0.63	0.03	0.08	0.88
Germany	0.77	0.46	0.66	0.02	0.06	0.43
Ghana	0.05	0.91	0.04	0.56	0.39	0.55
Greece	0.60	0.79	0.50	0.14	0.11	0.21
Guinea	0.03	0.88	0.14	0.82	0.30	0.07
Hungary	0.44	0.83	0.35	0.09	0.09	0.45
Iceland	0.67	0.33	0.40	0.07	0.06	0.92
India	0.07	0.97	0.79	0.57	0.21	0.18
Indonesia	0.09	0.93	0.48	0.45	0.28	0.19
Iran	0.34	0.87	0.61	0.24	0.13	0.36
Ireland	1.07	0.41	0.08	0.08	0.03	0.19
Israel	0.66	0.72	0.29	0.02	0.09	1.18
Italy	0.79	0.66	0.71	0.04	0.09	0.52
Japan	0.72	0.79	0.87	0.03	0.08	0.40
Jordan	0.19	0.44	0.42	0.08	0.28	0.38
Kazakstan	0.22	0.91	0.28	0.16	0.10	0.40
Kenya	0.04	0.90	0.52	0.73	0.30	0.14
Kyrgyzstan	0.06	0.95	0.25	0.39	0.38	0.75
Laos	0.05	0.97	0.35	0.76	0.30	0.18
Latvia	0.31	0.48	0.18	0.11	0.13	0.35
Lebanon	0.34	0.54	0.52	0.08	0.26	0.76
Lithuania	0.39	0.45	0.36	0.10	0.17	0.46

Macedonia	0.35	0.73	0.30	0.20	0.26	0.58
Malawi	0.02	0.95	0.21	0.81	0.21	0.11
Malaysia	0.30	0.49	0.30	0.16	0.09	0.49
Mauritius	0.22	0.48	0.28	0.10	0.18	0.59
Mexico	0.36	0.81	0.31	0.19	0.17	0.17
Moldova	0.10	0.80	0.06	0.41	0.24	0.36
Morocco	0.09	0.79	0.48	0.29	0.22	0.42
Mozambique	0.01	0.88	0.49	0.82	0.43	0.08
Nepal	0.03	0.97	0.68	0.75	0.41	0.19
New Zealand	0.54	0.82	0.65	0.08	0.08	0.62
Nigeria	0.06	0.98	0.41	0.70	0.41	0.21
Norway	1.32	0.68	0.51	0.04	0.05	0.38
Pakistan	0.10	0.92	0.74	0.41	0.39	0.39
Paraguay	0.10	0.91	0.52	0.27	0.25	0.67
Peru	0.20	0.81	0.76	0.26	0.20	0.22
Poland	0.42	0.85	0.59	0.19	0.13	0.20
Portugal	0.48	0.62	0.52	0.11	0.11	0.23
Qatar	2.14	0.06	0.21	0.01	0.03	0.10
Russia	0.29	0.78	0.73	0.09	0.14	0.52
Rwanda	0.02	0.95	0.60	0.79	0.34	0.17
Saudi Arabia	0.73	0.47	0.60	0.07	0.07	0.43
Senegal	0.04	0.32	0.44	0.72	0.40	0.08
Slovenia	0.54	0.68	0.27	0.09	0.08	0.29
South Africa	0.22	0.84	0.71	0.08	0.13	0.33
South Korea	0.59	0.83	0.76	0.07	0.08	0.44
Spain	0.68	0.67	0.64	0.06	0.08	0.55
Sri Lanka	0.12	0.45	0.60	0.44	0.28	0.17
Sudan	0.08	0.97	0.54	0.56	0.44	0.36
Sweden	0.76	0.61	0.49	0.03	0.06	0.46
Tajikistan	0.08	0.91	0.41	0.31	0.46	0.71
Thailand	0.15	0.84	0.52	0.53	0.10	0.10
Togo	0.02	0.78	0.14	0.57	0.49	0.50
Tunisia	0.20	0.75	0.47	0.22	0.19	0.39
Turkey	0.45	0.96	0.64	0.36	0.17	0.21
Ukraine	0.15	0.92	0.62	0.12	0.22	0.83
United Kingdom	0.77	0.55	0.54	0.02	0.05	0.41
United States	1.00	0.86	0.75	0.02	0.05	0.67
Uruguay	0.29	0.46	0.62	0.12	0.15	0.86
Venezuela	0.30	0.87	0.79	0.06	0.14	0.61
Vietnam	0.05	0.85	0.49	0.65	0.20	0.14
Yemen	0.11	0.69	0.45	0.44	0.28	0.15

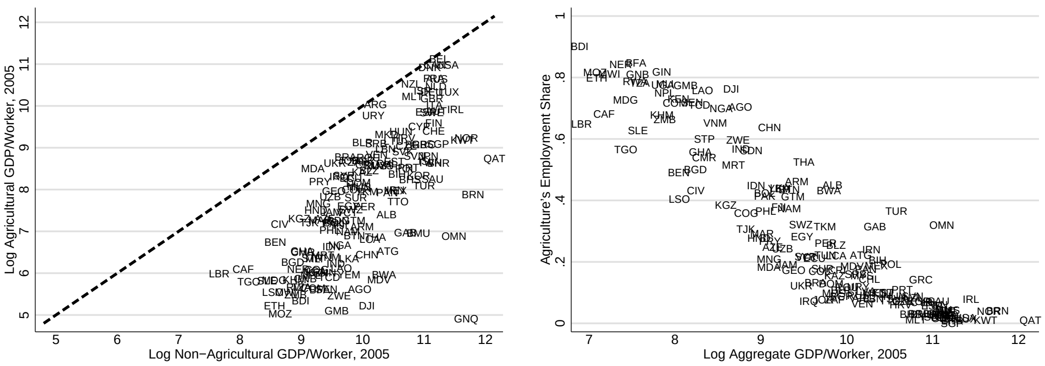
2.4 Key Empirical Patterns for All Possible Countries

Section 2 of the main paper is restricted to my sample of 90 countries outlined in appendix section 2.3. None of the patterns are particular to this sample. In this section, I replicate all of the figures from section 2 for the broadest possible set of countries for each. Keep in mind the countries included may vary from one figure to the next.

2.4.1 Labour Productivity

Figure 1 displays the results for 158 countries with sufficient data. Agricultural labor productivity differences are an order of magnitude greater than non-agricultural. Agricultural productivity among the richest 10% of countries is nearly 90 times higher than among the poorest 10%; the comparable figure is only 14 for non-agriculture. Other measures of variation give similar results. The 90/10 ratio for agriculture is 70 while the ratio for non-agriculture is 9. Despite such low productivity, the vast majority of poor country employment is agricultural, as illustrated in panel (b) of Figure 1.

Figure 1: Labor Productivity and Employment



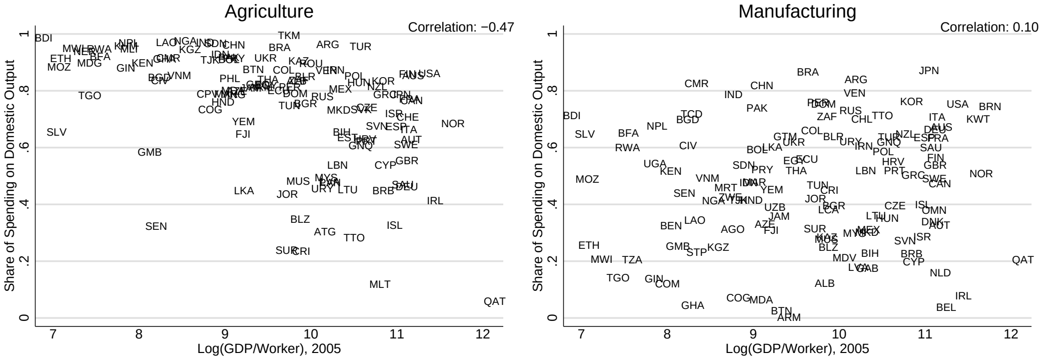
(a) Real Labor Productivity

(b) Agriculture's Share of Employment

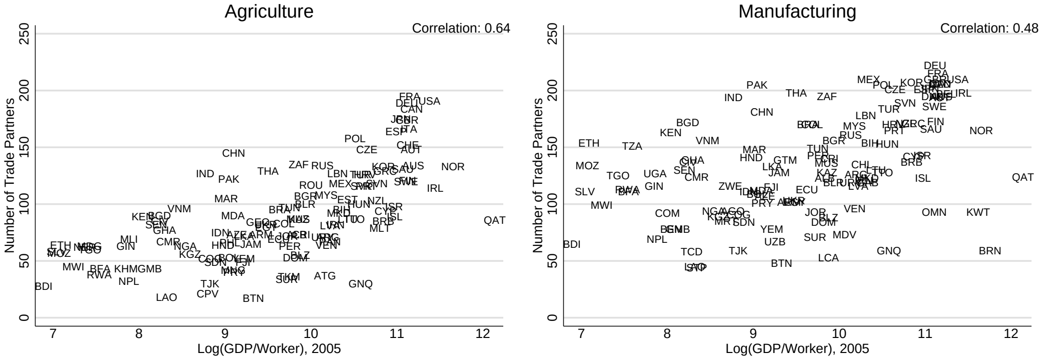
Labor productivity measured in international prices for agriculture and non-agriculture. Calculations follow Caselli (2005) and Restuccia et a. (2008). Agriculture's share of employment primarily from the UN-FAO. Details in appendix.

Figure 2: Key Trade Patterns for Agriculture and Manufacturing

(a) Share of Total Expenditures on Domestically Produced Goods



(b) Number of Trading Partners



Displays the share of total expenditures allocated to domestically produced goods (π^j_{nn}). Trading partners is the number number of exporters from which each country imports. Trade data are from CEPII's BACI database and production data are from the UNIDO, OECD, and FAO. All data is for 2005.

2.4.2 International Trade Patterns

What fraction of a country's total expenditures are spent on imports? The pattern of trade differs substantially across countries and sectors. Figure 2 displays home shares for agriculture (140 countries) and manufacturing (128 countries). Among the poorest countries, the share of agricultural expenditures allocated to domestically produced goods is well over 90%. While among rich countries the share is highly variable, the average is closer to 50%. For manufacturing goods, the pattern is very different. There is little relationship between π^m_{nn} and a country's level of development, with home share ranging between 40-50%.

The lack of agricultural trade by poor countries is also evident in the number of trading partners each country has. Counting the number of partners from which each country imports reveals a strong positive relationship between the number of trade partners and a country's level of development. In agriculture, poor countries typically import (what little they do import) from 50 sources while rich countries import from closer to 200. For manufacturing, the positive relationship still holds, though it is far less pronounced. Poor countries have between 100-150 partners for manufactured goods imports.

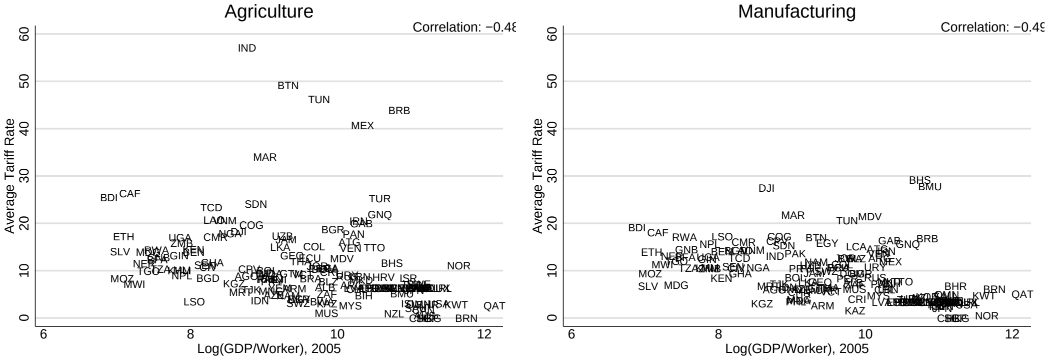
2.4.3 Trade Costs

Why do poor countries import so little food despite having such low productivity in that sector? Trade costs are an obvious candidate, though they come in many forms and are difficult to measure. First, consider average tariff levels. Trade-weighted average MFN tariff rates are available from the UN-TRAINS database, classified by sector using the HS codes listed earlier. I plot these tariffs in Figure 3 for 151 countries. While poor countries do have larger average tariffs than rich countries, the magnitudes are fairly small at 15-20% among the poorest countries compared to less than 5% among the richest.

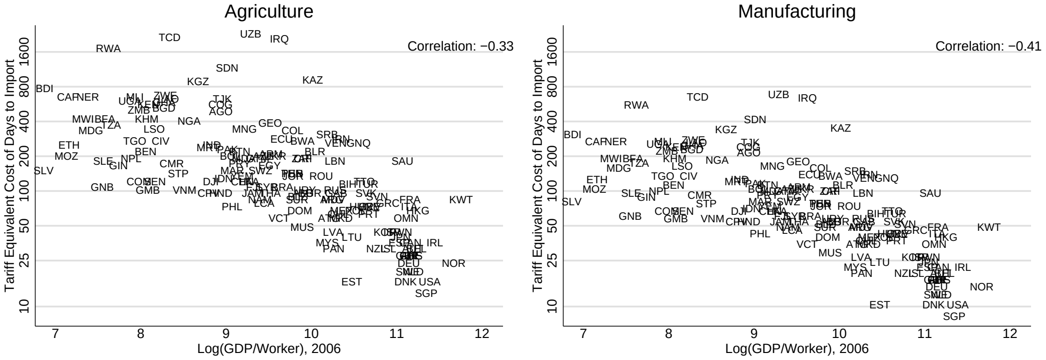
Trade costs go beyond tariffs; non-tariff barriers and other costs are far more important. Consider border delays. For perishable agricultural goods, these long delays may be particularly costly. Hummels and Schaur (2013) recently estimate the ad-valorem cost of time to import. They find for food and beverages each day is equivalent to a 3.1% tariff, compared to 2% for consumer and capital goods generally. Using their estimates, I construct a measure of the overall trade costs in agriculture and manufacturing associated with time delays. Panel (b) of Figure 3 plots the results of this calculation for 119 countries for agriculture 128 countries for manufacturing. The difference in magnitude between rich and poor countries is stark. On average, the ad-valorem cost of time delays to import into poor countries is approximately 400% in agriculture and 200% in manufacturing. The time cost for rich countries are an order of magnitude lower, varying around 30% for agriculture and 20% for manufacturing.

Figure 3: Trade Costs in Agriculture and Manufacturing

(a) Average Tariff Rates



(b) Time Costs to Import

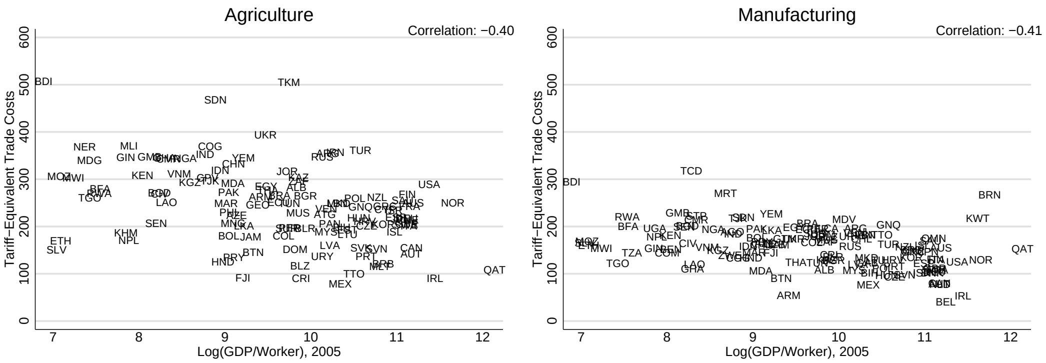


Displays observable measures of trade costs in agriculture and manufacturing. First, observable trade-weighted MFN tariffs from UN-TRAINS. Second, the ad-valorem equivalent cost of border delays. Days to import are from the World Bank Doing Business Index for 2006 (2005 is unavailable). The results of Hummels and Schaur (2013) suggest a tariff-equivalent cost of 3.1% per day for food and beverages, and roughly 2% per day for consumer and capital goods. These rates are used to convert the single Days to Import variable to ad-valorem rates that differ by sector.

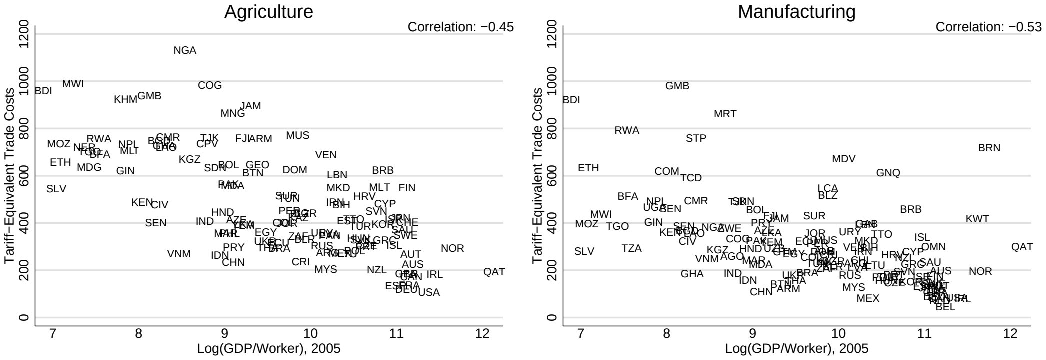
Beyond these observable measures, Novy (2013) generalizes Head and Ries (2001) to provide an aggregate summary measure of bilateral trade costs. Following the main text, I construct this measure (include asymmetries) for many countries. Specifically, I measure agricultural export costs t_n^a for 123 countries and manufacturing export costs t_n^m for 141. I summarize these in Figure 4 as the trade-weighted average across country pairs. The top panel reports the average cost by importer; the bottom panel, by exporter. Poor countries systematically face higher trade costs,

Figure 4: Trade Costs in Agriculture and Manufacturing

(a) Average Trade Costs, by Importer



(b) Average Trade Costs, by Exporter



Displays trade costs in agriculture and manufacturing. The top panel averages trade costs τ_{ni}^{j} across all exporters *i* for each importer *n*, weighted by trade volumes. The bottom panel averages across importers for each exporter.

particularly in agriculture. The typical poor countries faces import costs of approximately 300% in agriculture and 150-200% in manufacturing. The average cost of exporting for these countries is even higher.

3 Calibration Details

This section outlines details behind calibrating the production function parameters and the elasticity of trade. I also provide a brief set of results that confirms Waugh

(2010)'s results hold for agricultural trade, which justifies using an export-cost specification for trade-cost asymmetries.

3.1 Production Function Parameters

To calibrate each sector's production function parameters ($\beta, \phi^j, \gamma^{jk} \forall j,k \in \{a,m,s\}$), I use data from the Input-Output tables in the OECD Structural Analysis Database. From this, I construct measures of total output, value-added, and spending on various inputs by sector for the mid-2000s. Industries are classified by ISIC Revision 3, with Agriculture as 01-09, Manufacturing as 15-39, and Services as 40-95. Mining, quarrying, and raw materials sectors (10-14) are not included in this exercise, as I do not included these sectors in the trade flow measures of the paper. Countries included in the database are typically rich but there is also data for certain poor countries, including India and China, and middle-income countries, such as Turkey, South Africa, and Mexico.

To estimate labor's share of value-added, I treat a share of gross operating surplus as labor compensation. This is common in the literature and accounts for the labor of owner operators that are not paid in wages (see, for example, Gollin, 2002). I use a higher share of surplus as labor compensation in agriculture than in manufacturing or services. To reach an aggregate share of nearly two-thirds, I assume 40% of agricultural surplus is labor compensation while I assume 25% for manufacturing and services.

This adjustment is not without consequence, although it is necessary. Labor compensation, as reported, implies labor's share of value added is 0.29 in agriculture and 0.53 in aggregate. These values are inconsistent with other evidence and are therefore not likely correct. Consider measures of input use compiled by Fuglie (2010). Aggregating various studies, he finds a worldwide average agricultural labor inputs relative to gross output of 0.35. The share of land and structures is 0.21, suggesting labor's share of value-added of 0.63. His evidence also suggests little variation across countries. More broadly, Gollin (2002) finds little variation in labor's aggregate share of value-added across countries. Since a country's employment share in agriculture does vary with income, labor's share of value added

Table 2: Production Function Parameters

		Sector j		
		Agriculture	Manufacturing	Services
Labor's Share of Value Added	β	0.65	0.65	0.65
Value Added Share of Output	ϕ^j	0.50	0.35	0.59
Agricultural Input's Share	γ^{ja}	0.31	0.06	0.01
Manufactured Input's Share	γ^{jm}	0.39	0.61	0.24
Services Input's Share	γ^{js}	0.30	0.33	0.75

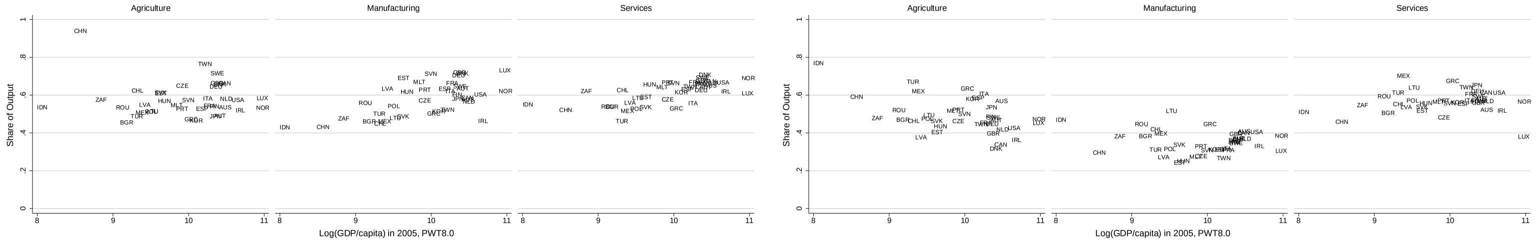
Displays the production-weighted average share of labor in value-added, value-added in output, and the intermediate inputs sources for three broad sectors from the OECD STAN Input-Output (Total) tables for mid-2000s. Industries are classified by ISIC Revision 3, with Agriculture as 01-09, Manufacturing as 15-39, and Services as 40-95.

across sectors must be close to equal. Gollin, Lagakos and Waugh (2014) review more evidence on this point.

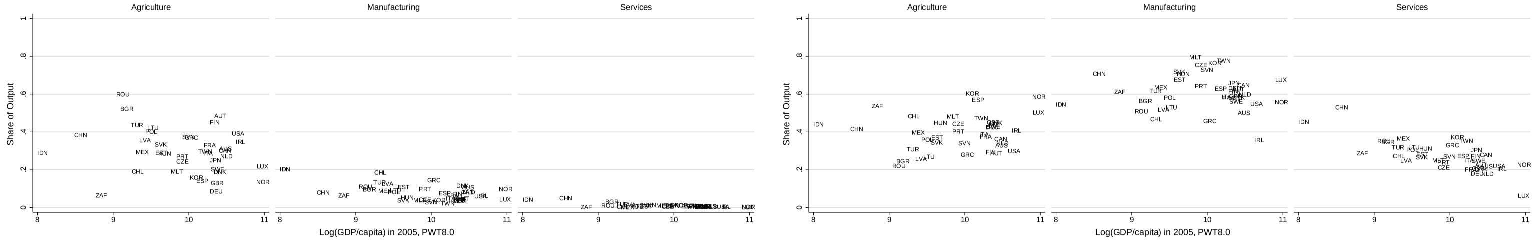
I report the production-weighted average values in Table 2. The importance of intermediate inputs varies across sectors. The value-added to gross output ratio in services is nearly double that in manufacturing and roughly 50% in agriculture. The source of intermediates also varies substantially across sectors. Agriculture demands inputs from the three sectors in roughly even proportion. Manufacturing and services demand almost no agricultural inputs (and what little agricultural inputs manufacturing uses is largely due to food and beverage processing). Own-sector inputs are, by far, the most important intermediates for non-agricultural sectors.

The shares are fairly uniform across different levels of development. To show this, I plot the country-specific shares against per-capita GDP in various figures. Figure 5 (a) plots labor's share of value added across countries and sectors. With the exception of China, all countries are very close to the aggregate share of two-thirds. Figure 5 (b) gives the same plot for the value-added share of gross output. Finally, Figures 5 (c)-(e) display the intermediate input shares. This evidence suggests using the same production function parameters across countries is empirically reasonable.

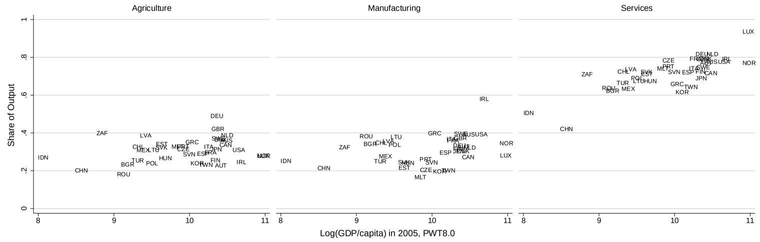
Figure 5: Input Shares, by Sector and Country (OECD STAN Data)


(a) Labor's Share of Value-Added

(b) Value-Added Share of Gross Output


(c) Agricultural Inputs' Share of Intermediates

(d) Manufactured Inputs' Share of Intermediates


(e) Services Inputs' Share of Intermediates

3.2 Estimating Productivity Dispersion θ

Firm productivities in sector j are distributed Frechet following the CDF $F(x) = e^{-(x/A_i^j)^{-\theta^j}}$, where larger θ^j implies smaller variance. In Eaton-Kortum trade models, differences in firm productivity provide the incentive to trade. Recall the expression,

$$\pi_{ni}^j = \left(P_n^j\right)^{\theta^j} \left(\frac{\tau_{ni}^j c_i^j \gamma}{A_i^j}\right)^{-\theta^j}.$$

Greater differences leads to less sensitivity of trade flows to trade costs, as goods are less substitutable. This relationship between trade flows and trade costs can help identify θ^j. The difficulty lies in finding measures for overall productivity A_i^j, prices P_n^j, input costs c_i^j, and trade costs τ_{ni}^j.

The country-specific factors in this expression can be canceled by taking differences between pairs of countries. Specifically,

$$ln\left(\frac{\pi_{ni}^j}{\pi_{in}^j}\frac{\pi_{ih}^j}{\pi_{hi}^j}\frac{\pi_{hn}^j}{\pi_{nh}^j}\right) = -\theta^j ln\left(\frac{\tau_{ni}^j}{\tau_{in}^j}\frac{\tau_{ih}^j}{\tau_{hi}^j}\frac{\tau_{hn}^j}{\tau_{nh}^j}\right).$$

The challenge to estimate θ^j is now to find a measure of the trade cost ratios on the right hand side.

Following Caliendo and Parro (2012), consider overall trade costs τ_{ni}^j as a composite of importer-specific costs μ_n^j, such as border delays or other non-tariff barriers; exporter-specific costs δ_i^j, which Waugh (2010) finds particularly important for developing countries; symmetric bilateral trade costs ν_{ni}^j that inhibit trade between two countries in a similar way, such as distance, language, regional trade agreements, and so on; and, finally, asymmetric bilateral trade costs t_{ni}^j that may be different for trade from country i to n than from n to i. Tariffs are an important component of asymmetric bilateral trade costs. Trade costs can then be modeled fairly generally as $ln\ \tau_{ni}^j = ln\ t_{ni}^j + \nu_{ni}^j + \mu_n^j + \delta_i^j + \varepsilon_{ni}^j$, and therefore

$$ln\ \frac{\tau_{ni}^j}{\tau_{in}^j} = ln\ \frac{t_{ni}^j}{t_{in}^j} + \mu_n^j - \mu_i^j + \delta_i^j - \delta_n^j + \varepsilon_{ni}^j - \varepsilon_{in}^j$$

does not depend on symmetric bilateral trade costs. This hold for all other countries pairs,

$$ln\,\frac{\tau^j_{ih}}{\tau^j_{hi}} = ln\,\frac{t^j_{ih}}{t^j_{hi}} + \mu^j_i - \mu^j_h + \delta^j_h - \delta^j_i + \varepsilon^j_{ih} - \varepsilon^j_{hi}$$

and

$$ln\,\frac{\tau^j_{hn}}{\tau^j_{nh}} = ln\,\frac{t^j_{hn}}{t^j_{nh}} + \mu^j_h - \mu^j_n + \delta^j_n - \delta^j_h + \varepsilon^j_{hn} - \varepsilon^j_{nh}.$$

Adding the above three expressions eliminates all country-specific costs,

$$ln\left(\frac{\tau^j_{ni}}{\tau^j_{in}}\frac{\tau^j_{ih}}{\tau^j_{hi}}\frac{\tau^j_{hn}}{\tau^j_{nh}}\right) = ln\left(\frac{t^j_{ni}}{t^j_{in}}\frac{t^j_{ih}}{t^j_{hi}}\frac{t^j_{hn}}{t^j_{nh}}\right) + \tilde{\varepsilon}^j_{ni},$$

where $\tilde{\varepsilon}^j_{ni} = \varepsilon^j_{ni} - \varepsilon^j_{in} + \varepsilon^j_{hi} - \varepsilon^j_{hi} + \varepsilon^j_{nh} - \varepsilon^j_{hn}$. The sum of first differences in (log-) trade costs between any three countries will depend only on the asymmetric trade costs between them. These asymmetric trade costs can be measured with data on bilateral tariff rates, which display large asymmetries.

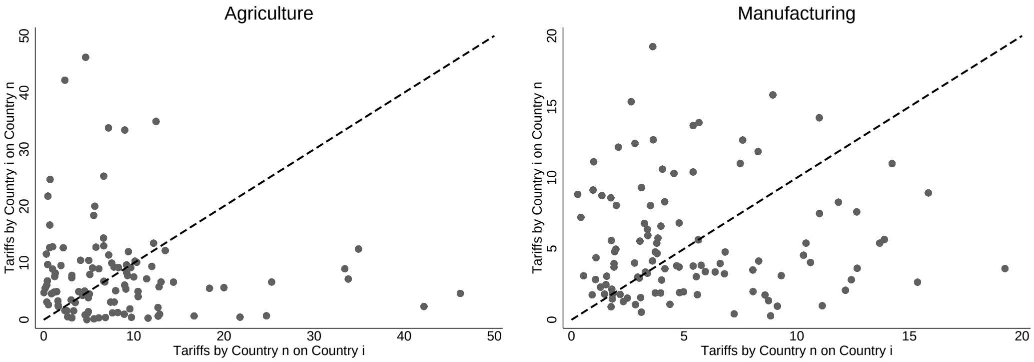
Combining this result with the relationship between trade flows and trade costs derived above,

$$ln\left(\frac{\pi^j_{ni}}{\pi^j_{in}}\frac{\pi^j_{ih}}{\pi^j_{hi}}\frac{\pi^j_{hn}}{\pi^j_{nh}}\right) \quad = \quad -\theta^j ln\left(\frac{t^j_{ni}}{t^j_{in}}\frac{t^j_{ih}}{t^j_{hi}}\frac{t^j_{hn}}{t^j_{nh}}\right) + \varepsilon^j_{ni},$$

where $\varepsilon^j_{ni} = -\theta^j\tilde{\varepsilon}^j_{ni}$. If other factors affecting trade flows ε^j_{ni} are unrelated to tariffs between countries, then this expression can be used to estimate θ^j.

To estimate θ^j from the above expression. Complete trade and tariff data on all country triples (i,n,h) are required. I investigate a number of country combinations. The "Parro Set" countries are those in Parro (2013), who finds $\theta = 4.6$ for capital goods and $\theta = 5.2$ for other manufactured goods in 1990. As I am using data on tariffs and trade for 2005, Finland and Sweden are aggregated into the EU. This set is presented for comparison to his results. My preferred estimates use a different set of countries: the biggest ten countries trading entities for which I have complete tariff and trade data. For agriculture, I include the European Union, the United States, Japan, China, Canada, Brazil, Mexico, Australia, Russia, and Argentina.

Figure 6: Tariff Asymmetries in Agriculture and Nonagriculture, 2005



For non-agriculture, I include the European Union, the United States, China, Japan, Canada, Korea, Taiwan, Mexico, Russia, and India. All remaining countries are aggregated into a "rest of the world" category.

I use data on (trade-weighted) average tariffs in agriculture and manufacturing from the UN-TRAINS database. Similar to how I define trade flows, agricultural tariffs are for products with two-digit HS codes 15 and below and manufactured products are products with codes 16-24 and 28-98. Raw materials (codes 25-27) are excluded. The asymmetries are evident in a plot of t^j_{ni} against t^j_{in} for all countries pairs in my data. Figure 6 displays this for a large set of countries. If Canada, for example, applies the same tariff against imports from the EU as the EU levies on imports from Canada, then the Canada-EU pair will fall on the figure's 45° line. Most trading relationships feature asymmetric tariff rates.

The resulting estimates in Table 3 are largely consistent with other estimates in the literature. For the same set of countries as Parro (2013), I find $\theta^m = 5.28$. Using the big-10 countries, I find $\theta^m = 4.63$.[2] For agricultural goods, I estimate a slightly smaller elasticity, at $\theta^a = 4.06$. Based on these results, I set $\theta^m = 4.63$ and $\theta^a = 4.06$.

Caliendo and Parro (2012) apply this method to trade flows between Canada,

---

[2] Other combinations of countries yield similar results. For the largest 15 countries, I find $\theta = 4.42$, and for the largest 20 countries, I find $\theta = 4.65$. The number of observations for the main regression is 990, since there are ten countries plus the rest of the world, which implies there are $(11)(10)(9) = 990$ triples.

Table 3: Productivity Dispersion Estimates, Agriculture and Manufacturing, 2005

	Manufacturing		Agriculture
	Parro Set	Top 10	Top 10
$\hat{\theta}^j$	5.27***	4.63***	4.06***
	[0.315]	[1.267]	[0.512]
Countries	18	10	10
Observations	5814	990	990
R^2	0.07	0.03	0.05

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

the United States, and Mexico in 1993 (pre-NAFTA). For agriculture, they find a larger estimate of $\theta^a = 8.11$. It is not surprising that the degree of productivity dispersion between producers in economies is less than for a large set of countries at various levels of development. Waugh (2010), for example, finds a larger value for θ among OECD countries than among non-OECD countries. Also, Caliendo and Parro (2012) estimate this parameter for a agricultural trade at a more disaggregated level and report the average whereas I estimate it for agricultural trade flows as a whole.

3.3 Trade Cost Asymmetries

Novy (2013) generalized the Head and Ries (2001) summary measure of trade costs. In a broad class of trade models, the average cost of trade between two countries is

$$\bar{\tau}^j_{ni} \equiv \sqrt{\tau^j_{ni}\tau^j_{in}} \quad = \quad \left(\frac{\pi^j_{nn}\pi^j_{ii}}{\pi^j_{ni}\pi^j_{in}}\right)^{\frac{1}{2\theta^j}}, \tag{3}$$

where $\bar{\tau}^j_{ni}$ is the geometric average cost for sector j trade (in both directions) between countries n and i, π^j_{ni} are the expenditure shares defined earlier, and θ^j is the (negative) cost-elasticity of trade. This measure is symmetric by construction ($\bar{\tau}^j_{ni} = \bar{\tau}^j_{in}$). But, trade cost asymmetries are known to be important. Waugh (2010), for example, demonstrates that poor countries systematically face higher export costs (regardless of the destination) than rich countries in manufacturing.

To measure trade cost asymmetries and adjust $\bar{\tau}^j_{ni}$ is straightforward. In the same broad class of trade models for which equation 3 holds, a gravity relationship

$$ln\left(\frac{\pi^j_{ni}}{\pi^j_{nn}}\right) = S^j_i - S^j_n - \theta^j ln\left(\tau^j_{ni}\right)$$

exists, where S^j denotes a country's sector j competitiveness (productivity, factor prices, and the like). Suppose trade costs τ^j_{ni} depend in part on common bilateral components such as distance, shared border, and shared language. Further suppose there is a country-specific additional cost of trading. In the main text, I follow Waugh (2010) and presume this country-specific cost is an export cost. The alternative is to assume it is an import cost.

For either assumption, one can measure the country-specific cost with the following regression

$$ln\left(\frac{\pi^j_{ni}}{\pi^j_{nn}}\right) = \beta^{j\prime}\mathbf{X}_{ni} + \iota^j_n + \eta^j_i + \varepsilon^j_{ni},$$

where $\mathbf{X}_{ni}$ is a matrix of observable bilateral components, ι^j_n and η^j_i are a set of importer and exporter fixed-effects, respectively. The country-specific trade cost is inferred from fixed effects. They are both of the same magnitude, despite applying to trade flows in different directions. Specifically, $ln\ t^j_n = -(\iota^j_n + \eta^j_n)/\theta^j$. Combining the export cost estimates with equation 3 yields a measure of trade costs $\tau^j_{ni} = \bar{\tau}^j_{ni}(t^j_i/t^j_n)^{1/2}$. If country-specific costs are import costs, then $\tau^j_{ni} = \bar{\tau}^j_{ni}(t^j_n/t^j_i)^{1/2}$ instead.

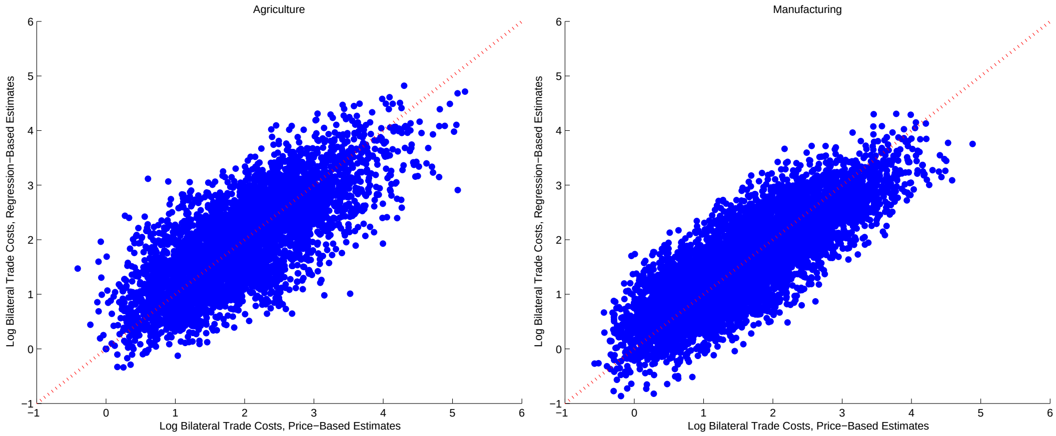
How do we know which to use? One can use additional data to learn about the nature of the trade cost asymmetries. Waugh (2010) demonstrates that in the same broad class of models for which the above regression holds, we have

$${\tau^j_{ni}}^P = \left(\frac{P^j_n}{P^j_i}\right)\left(\frac{\pi^j_{ni}}{\pi^j_{ii}}\right)^{-1/\theta^j},$$

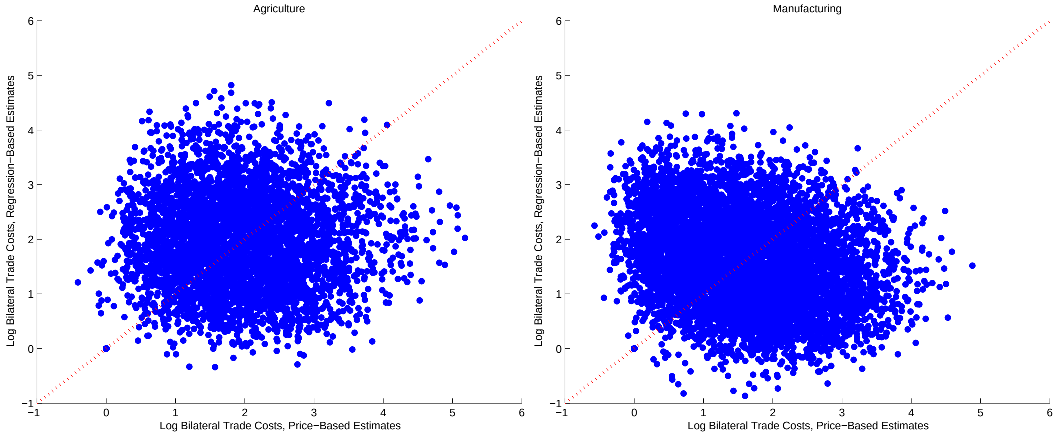
where P^j_n is the price index for sector j goods. For countries surveyed, one can use the World Bank 2005 ICP cross-country price data to proxy for P^j_n. We can

Figure 7: Comparing Regression-Based to Price-Based Estimates

(a) Export Cost Specification



(b) Import Cost Specification



use this price-based estimate of trade costs to see which regression-based estimate correlates most strongly.

Figure 7 compares these estimates. On the horizontal axis, I plot the price-based estimates ${\tau_{ni}^{j}}^{P}$ and on the vertical axis I plot the regression-based estimates. The export cost specification is the top panel and the import cost specification is the bottom panel. It is clear that there is a strong positive correlation between the export cost specification and the price-based estimates. This is true in manufacturing (as Waugh, 2010, demonstrated) and it is equally true in agriculture. The import cost specifications display essentially no correlation – and even slightly negative for manufacturing. So, I opt for an export cost specification to augment the symmetric trade cost estimates $\bar{\tau}_{ni}^{j}$ from the Head-Reis-Novy approach.

4 Alternative Model Specifications

This section reports various robustness exercises to ensure the main results of the paper are not overly sensitive to certain modeling choices. Each alternative specification was discussed and introduced in the main text. I display the results, for the poorest 10% of countries, in Table 4. The first column corresponds to a higher value for agriculture's θ parameter. This means the variation in agricultural productivity is lower (and therefore the gains from trade liberalization are lower) than in the baseline model of the paper. The second column shuts down inter-sectoral linkages (and all intermediate inputs) and abstracts from non-labour inputs. The third column uses alternative preference parameters estimated by Herrendorf et al. (2013). In all cases, the broad results of the main paper hold. Namely, a large share of cross-country productivity differences can be accounted for by trade barriers as agricultural productivity grows substantially upon liberalization and labor reallocates to non-agricultural employment.

The final two columns require additional discussion, to which I turn in the next two sections.

4.1 Eliminating Initial Zeros from the Trade Matrix

There are often potential trade relationships that are not realized, or that do not have trade volumes available in the data. For example, Canada did not record any agricultural exports to Bhutan in 2005 in the data. The presence of zeros in the trade data is well known phenomenon.

To ensure these are not driving any of the main results of the paper, I replace zeros with imputed trade values following a simple gravity-regression approach.

Table 4: Results for Poor Countries, Various Alternative Specifications

	Agriculture					Both Sectors				
	$\theta^a = 8$ $\theta^m = 5$	$\beta = 1$ $\phi^j = 1$	$\varepsilon^a = 0.02$, $\varepsilon^m = 0.15$, $\varepsilon^s = 0.83$	No Zeros	Unbalanced Trade	$\theta^a = 8$ $\theta^m = 5$	$\beta = 1$ $\phi^j = 1$	$\varepsilon^a = 0.02$, $\varepsilon^m = 0.15$, $\varepsilon^s = 0.83$	No Zeros	Unbalanced Trade
Change in Welfare										
Total Welfare	67.0%	106.3%	116.5%	127.4%	72.4%	638.6%	364.7%	470.1%	607.3%	381.6%
Real Wage Effect	29.7%	17.2%	38.4%	55.8%	14.5%	88.3%	53.9%	91.4%	144.4%	88.9%
Labor Market Effect	-7.1%	20.3%	5.3%	-3.4%	14.0%	156.1%	99.7%	94.7%	87.0%	95.7%
Subsistence Effect	38.6%	46.3%	48.5%	51.1%	43.6%	53.1%	51.2%	53.0%	54.8%	52.0%
Change in Productivity										
Aggregate	74.6%	152.3%	220.6%	303.3%	98.9%	800.8%	378.1%	767.0%	940.4%	480.5%
Agricultural	243.5%	381.1%	774.8%	1027.2%	343.2%	596.3%	462.7%	1417.9%	1703.2%	665.9%
Manufacturing	96.3%	87.3%	207.1%	232.3%	56.4%	1009.1%	470.6%	1604.0%	1738.5%	799.9%
Services	13.1%	0.0%	16.2%	21.0%	3.1%	7.7%	0.0%	24.7%	27.6%	13.5%
Change in Employment and Trade Shares (p.p.)										
Ag Employment	2.6	-8.5	-3.2	0.8	-8.2	-67.0	-37.1	-42.2	-38.2	-44.0
Ag Home Trade	-91.6	-91.3	-91.4	-91.4	-90.2	-91.7	-91.5	-91.6	-91.5	-91.2
Mfg Home Trade	-31.6	-38.8	-38.6	-39.6	-21.2	-44.7	-44.7	-44.7	-44.7	-44.7
Aggregate Productivity Ratio, Rich/Poor (Data: 40.9)										
Counterfactual Ratio	25.8	18.6	16.1	12.9	25.1	8.4	11.9	9.1	8.2	14.3
Share Explained	0.12	0.21	0.25	0.31	0.13	0.43	0.33	0.41	0.43	0.28

Reports main counterfactual of the main paper (eliminating trade costs in agriculture and in both sectors) under various alternative specifications. The effects for the bottom 10% of countries are reported.

For country pairs for which trade data is non-zero, I estimate

$$ln\left(\frac{\pi^j_{ni}}{\pi^j_{nn}}\right) = \beta^{j\prime}\mathbf{D}_{ni} + b_{ni} + l_{ni} + ln(t^j_{ni}) + \iota^j_n + \eta^j_i + \varepsilon^j_{ni},$$

where $\mathbf{D}_{ni}$ is a vector of distance dummies, b_{ni} is a shared border dummy, l_{ni} indicates a shared language, t^j_{ni} is the tariff levied by country n on sector j goods from country i, and ι^j_n and η^j_i are importer and exporter fixed effects. I report the results of this regression in Table 5. The coefficients are not of direct interest to this exercise, so I do not comment on them here. They are simply used to infer trade values for the bilateral pairs for which trade data reports zero. From these inferred values for $ln(\pi^j_{ni}/\pi^j_{nn})$, it is straightforward to find $\hat{\pi}^j_{ni}$. Let $\tilde{\pi}^j_{ni} = \pi^j_{ni}/\pi^j_{nn}$ be the fitted values from the above regression. Given $\sum_{i=1}^N \pi^j_{ni} = 1$, we have $\hat{\pi}^j_{ni} = \tilde{\pi}^j_{ni}/\left(\sum_{i=1}^N \tilde{\pi}^j_{ni}\right)$. With these new values for trade shares, I can also impute trade costs using the Novy-Head-Reis method described in the paper.

With the zeros replaced with imputed values, I repeat the main quantitative exercises of the paper and report the results in the fourth (and eighth) column of Table 4. As before, the results are robust. If anything, the productivity gains from lower trade costs are larger with zeros in the trade data. This is not surprising, as countries can now respond to changes in trade costs with more countries. In the main exercises of the paper, any country pair with zero initial trade *must* have zero trade in any of the counterfactuals. With the additional flexibility here, gains are larger for any given reduction in trade costs.

4.2 Unbalanced Trade

In the main model and results, I allow for trade surpluses or deficits at the sector level. Agricultural exports, for example, need not equal agricultural imports. At the country-level, trade must balance. Any deficit in one sector must be exactly offset by a surplus in the other. Allowing for unbalanced aggregate trade is straightforward. Dekle et al. (2007) incorporate exogenous cross-country financial transfers to generate unbalanced trade and I follow their approach.

Countries that receive a transfer can sustain a trade deficit, while countries that

Table 5: Gravity Regression to Impute Missing Trade Values

	Dep. Var.: $ln\left(\pi^j_{ni}/\pi^j_{nn}\right)$	
	Agriculture	Manufacturing
Distance $<$ 1000 km	-10.35***	-8.094***
	[0.395]	[0.281]
Distance $\in [1000, 2500$ km	-12.08***	-9.737***
	[0.390]	[0.271]
Distance $\in [2500, 5000]$ km	-13.12***	-10.84***
	[0.394]	[0.274]
Distance $\in [5000, 7500]$ km	-14.07***	-11.64***
	[0.397]	[0.276]
Distance $\in [7500, 10000]$ km	-14.20***	-11.86***
	[0.395]	[0.276]
Distance $\in [10000, 15000]$ km	-14.48***	-12.35***
	[0.399]	[0.279]
Distance $>$ 15000 km	-15.20***	-12.52***
	[0.413]	[0.290]
Common Border	1.144***	0.920***
	[0.154]	[0.126]
Common Language	0.820***	1.123***
	[0.0927]	[0.0716]
Tariffs, $ln(t^j_{ni})$	-0.660**	-2.180***
	[0.283]	[0.401]
Importer FEs	Yes	Yes
Exporter FEs	Yes	Yes
Observations	5339	6879
R^2	0.959	0.967

Results of a gravity regression to impute missing bilateral trade values. The specification $ln\left(\frac{\pi^j_{ni}}{\pi^j_{nn}}\right) = \beta^{j\,\prime}\mathbf{D}_{ni} + b_{ni} + l_{ni} + ln(t^j_{ni}) + \iota^j_n + \eta^j_i + \varepsilon^j_{ni}$ is estimated separately for agriculture and manufactured goods. * p<0.1, ** p<0.05, *** p<0.01. Standard errors in parentheses.

provide a transfer must have a surplus. These transfers are exogenous and fixed across counterfactual experiments. For an aggregate surplus of country n of S_n, total income is

$$I_n = \phi^a R_n^a + \phi^m R_n^m + \phi^s R_n^s - S_n.$$

The balanced trade condition will also now reflect the aggregate surplus,

$$R_n^a + R_n^m = S_n + X_n^a + X_n^m.$$

All other aspects of the model remain unchanged.

I calibrate the value of a country's aggregate trade surplus S_n to match the surplus to GDP ratio found in data. Specifically, while solving for the initial equilibrium income I_n and sectoral revenues (R_n^a, R_n^m, R_n^s) I set $S_n = \eta_n I_n - \frac{1}{N}\sum_{i=1}^{N} \eta_i I_i$ where η_n is the sum of agricultural and manufacturing surpluses in the BACI data relative to aggregate expenditure-side GDP from the Penn World Table (version 8.0). The demeaning term in the S_n expression is necessary to ensure global trade imbalances sum to zero. With this initial value for S_n, I hold it fixed over all counterfactuals.

I repeat the main exercises of the paper with unbalanced trade that matches data, reporting the results in the fifth (and tenth) column of Table 4. Once again, the overall results are robust. Though slightly smaller in magnitude, agricultural trade costs still account for 13% of the aggregate productivity difference between rich and poor countries. Manufacturing and agricultural trade costs combined account for over one-quarter.

4.3 Tariff Revenue

Non-tariff barriers involve real resource costs associated with trade. Given the importance of NTBs, I abstracted from changes in tariff revenue rebates in the counterfactual exercises of the main paper. Essentially, I assumed any tariff revenue was thrown into the ocean. Incorporating tariff revenue into the main model adds a lot of structure with little change to the paper's main conclusions. There is an important difference in the welfare effect of lowering agricultural tariffs and lowering manufacturing tariffs. It turns out that lower manufacturing tariffs lowers poor country welfare when tariff revenue is accounted for. I will not discuss these results in too much detail, as Święcki (2013) carefully examines a country's tariff policy in a similar three-sector setting with distorted labor markets. The findings I report here are qualitatively consistent with his analysis.

To begin, we must augment the paper's main model to allow for tariff revenue rebates. To that end, I closely follow Caliendo and Parro (2012). Denote total tariff revenue as T_n. For each dollar spent by consumers in n on goods from i only $1/(1+t_{ni}^j)$ will go to producers in i and $t_{ni}^j/(1+t_{ni}^j)$ will go to the government of country n. Since we spend a total of $X_n^j \pi_{ni}^j$ dollars on goods from i, total tariff revenue from that source country is $X_n^j \pi_{ni}^j t_{ni}^j/(1+t_{ni}^j)$. Total tariff revenue from all sources is then

$$\begin{aligned} T_n &= X_n^a \sum_{i=1}^{N} \pi_{ni}^a \left(1 - \frac{1}{1+t_{ni}^a}\right) + X_n^m \sum_{i=1}^{N} \pi_{ni}^m \left(1 - \frac{1}{1+t_{ni}^m}\right), \\ &= X_n^a(1-F_n^a) + X_n^m(1-F_n^m), \end{aligned}$$

where $F_n^j \equiv \sum_{i=1}^N \pi_{ni}^j/(1+t_{ni}^j)$. Intuitively, this is similar to Alvarez and Lucas (2007), where $1-F_n^j$ represents the fraction of country n spending on sector j goods that goes to country n's government (as tariff revenue).

How does $F_n^j \neq 1$ change key model expressions? First, the representative household's total income must include tariff revenue T_n in addition to labor income and payments from other factors. Total factor payments still equal total value added $\sum j \in \{a,m,s\}\, \phi^j R_n^j$. So, income is $I_n = T_n + \sum j \in \{a,m,s\}\, \phi^j R_n^j$, which is equivalently expressed as $I_n = \beta^{-1} w_n L_n \lambda_n + T_n$.

The trade balance condition also changes. Total spending on imported sector j goods by country n is $X_n^j \sum_{i \neq n} \pi_{ni}^j$. Of this, only $\sum_{i \neq n} \pi_{ni}^j X_n^j/(1+t_{ni}^j)$ reaches producers abroad due to tariffs levied by country n on imports from i, denoted t_{ni}^j. Similarly, total spending by the rest of the world on country n goods is $\sum_{i \neq n} \pi_{in}^j X_i^j$. But, only $\sum_{i \neq n} \pi_{in}^j X_i^j/(1+t_{in}^j)$ reaches country n producers. Given a trade surplus S_n^j in sector j for country n, and total revenue $R_n^j = \sum_{i=1}^N \pi_{in}^j X_i^j/(1+t_{in}^j)$, it is straightforward to show $R_n^j = F_n^j X_n^j + S_n^j$. Summing across tradables, aggregate trade balance

Table 6: Counterfactual Elimination of Tariffs in Poorest 10% of Countries

	Lower Tariffs in		
	Agriculture	Manufacturing	Both Sectors
Change in Welfare			
Total Welfare	1.2%	-4.2%	-3.2%
Real Wage Effect	-0.8%	3.8%	3.1%
Labor Market Effect	1.6%	-3.0%	-1.6%
Subsistence Effect	0.9%	-1.9%	-1.1%
Change in Productivity			
Aggregate	1.1%	0.3%	1.4%
Agricultural	0.4%	2.9%	3.3%
Manufacturing	-1.3%	9.2%	7.9%
Services	-0.7%	2.2%	1.6%
Change in Employment and Trade Shares (p.p.)			
Ag Employment	-0.7	1.2	0.6
Ag Home Trade	-3.4	0.7	-2.5
Mfg Home Trade	0.8	-6.6	-6.0

Displays results of lower tariffs when changes in tariff revenue rebates to households are accounted for. The poorest 10% of countries have their tariffs set to zero in each sector while all other countries remain unchanged.

requires that for each country $R_i^a + R_i^m = F_n^a X_n^a + F_n^m X_n^m$.

With these changes to the model, one can examine the welfare effect of lowering tariffs and account for the lost household income. I focus on unilateral changes here (as global tariff reductions were reported in the main text) among the poorest 10% of countries. I present the results of these experiments in Table 6. Eliminating poor-country agricultural tariffs increases welfare by over 1% while eliminating manufactured goods tariffs decreases welfare by over 4% in the typical poor country. Together, the latter effect dominates and welfare declines by just over 3%. Aggregate productivity always grows.

What is behind these results? Liberalizing manufactured goods imports leads domestic manufacturing in poor countries to contract, reallocating workers to other sectors – including agriculture. Given labor distortions that lowers agriculture's relative wages, this reallocation lowers welfare. That labor market distortions can provide an incentive for poor countries to erect import barriers for manufactured goods is a result examined in more detail by Święcki (2013). Readers interested in further examination of this point should consult his paper.

References

Adamopoulos, Tasso, "Transportation Costs, Agricultural Productivity and Cross-Country Income Differences," *International Economic Review*, 2011, *52* (2), 489–521.

Caliendo, Lorenzo and Fernando Parro, "Estimates of the Trade and Welfare Effects of NAFTA," *NBER Working Paper*, 2012, (18508).

Caselli, Francesco, "Accounting for Cross-Country Income Differences," in Philippe Aghion and Steven Durlauf, eds., *Handbook of Economic Growth*, Vol. 1, Elsevier, 2005, chapter 9, pp. 679–741.

Dekle, Robert, Jonathan Eaton, and Samuel Kortum, "Unbalanced Trade," *American Economic Review*, May 2007, *97* (2), 351–355.

Fuglie, Keith, "Total factor productivity in the global agricultural economy: evidence from FAO data," in Julian Alston, Bruce Babcock, and Philip Pardey, eds., *The shifting patterns of agricultural production and productivity worldwide*, Midwest Agribusiness Trade Research and Information Center, Iowa State University, 2010, pp. 63–95.

Gaulier, Guillaume and Soledad Zignago, "BACI: International Trade Database at the Product-Level. The 1994-2007 Version.," *CEPII Working Paper, No. 2010-23*, 2010.

Gollin, Douglas, "Getting Income Shares Right," *Journal of Political Economy*, 2002, *110* (2), 458–474.

_ , David Lagakos, and Micheal Waugh, "The Agriculture Productivity Gap," *Quarterly Journal of Economics*, 2014, *192* (2).

Head, Keith and John Ries, "Increasing Returns versus National Product Differentiation as an Explanation for the Pattern of U.S.-Canada Trade," *American Economic Review*, 2001, *91* (4), 858–876.

Herrendorf, Berthold, Richard Rogerson, and Akos Valentinyi, "Growth and Structural Transformation," *Forthcoming: Handbook of Economic Growth*, 2013.

Hummels, David and Georg Schaur, "Time as a Trade Barrier," *American Economic Review*, 2013, *103* (7), 2935–2959.

Novy, Dennis, “Gravity Redux: Measuring International Trade Costs With Panel Data,” *Economic Inquiry*, 2013, *51* (1), 101–121.

Parro, Fernando, “Capital-Skill Complementarity and the Skill Premium in a Quantitative Model of Trade,” *American Economic Journal: Macroeconomics*, 2013, *5* (2), 72–117.

Rao, Presada, “Intercountry Comparisons of Agricultural Output and Productivity,” *FAO Economic and Social Development Papers*, 1993, *112.*

Restuccia, Diego, Dennis Tao Yang, and Xiaodong Zhu, “Agriculture and aggregate productivity: A quantitative cross-country analysis,” *Journal of Monetary Economics*, March 2008, *55* (2), 234–250.

Święcki, Thomasz, “Intersectoral Distortions, Structural Change, and the Welfare Gains from Trade,” 2013.

Waugh, Michael E., “International Trade and Income Differences,” *American Economic Review*, 2010, *100*, 2093–2124.