Supplemental Appendix: "The Dynamics of Agricultural Productivity Gaps: An Open-Economy Perspective" (Douglas Gollin, David Lagakos, Xiao Ma, Shraddha Mandi)

A Data Appendix

Table A.1: Countries and years with APG data

	Years of Data		
Country	APG	Model	HCAPG
Argentina	1970 1980 2001	1980 2001	1970 1980 2001
Armenia	2001 2011		
Austria	1971 1981 1991 2001 2011	1981 1991 2001 2011	
Bangladesh	1991 2001 2011	1991 2001 2011	1991 2001 2011
Belarus	1999 2009		
Benin	1979 1992 2002 2013	1992 2002 2013	
Bolivia	1976 1992 2001 2012	1992 2001 2012	
Botswana	1991 2001 2011		
Brazil	1970 1980 1991 2000 2010	1980 1991 2000 2010	1970 1980 1991 2000
Burkina Faso	1985 1996	1985 1996	
Cambodia	1998 2004 2008 2013	1998 2004 2008 2013	1998 2004 2008 2013
Cameroon	1976 2005	2005	1976 2005
Canada	1971 1981 1991 2001 2011	1981 1991 2001 2011	
Chile	1970 1982 1992 2002	1982 1992 2002	1970 1982 1992 2002
China	1982 1990 2000	1982 1990 2000	
Costa Rica	1973 1984 2000 2011	1984 2000 2011	1973 1984 2000 2011
Ecuador	1982 1990 2001 2010	1982 1990 2001 2010	1982 1990 2001 2010
Egypt	1986 1996 2006	1986 1996 2006	
El Salvador	1992 2007	1992 2007	1992 2007
Fiji	1976 1986 2014	1986 2014	
France	1975 1982 1990 1999	1982 1990 1999	
Ghana	1984 2000 2010	1984 2000 2010	1984 2000 2010

Table A.1 Continued: Countries and years with APG data

Greece	1971 1981 1991 2001 2011	1981 1991 2001 2011	
Guatemala	1973 1981 1994 2002	1981 1994 2002	1973 1981 1994 2002
Guinea	1983 1996 2014	1983 1996 2014	1983 1996 2014
Haiti	1971 1982 2003	1982 2003	
Honduras	1974 1988 2001	1988 2001	1974 1988 2001
Hungary	1970 1980 1990 2001 2011	1980 1990 2001 2011	
India	1983 1987 1993 1999 2004 2009	1983 1987 1993 1999 2004 2009	
Indonesia	1971 1976 1980 1985 1990 2000 2010	1980 1985 1990 2000 2010	
Ireland	1971 1981 1986 1991 1996 2002 2006 2011 2016	1981 1986 1991 1996 2002 2006 2011	
Israel	1972 1983 1995 2008	1983 1995 2008	
Jamaica	1982 1991 2001	1982 1991 2001	
Kyrgyz Republic	1999 2009		
Lesotho	1996 2006		
Liberia	1974 2008	2008	1974 2008
Malawi	1987 1998 2008	1987 1998 2008	1987 1998 2008
Malaysia	1970 1980 1991 2000	1980 1991 2000	1980 1991
Mali	1987 1998 2009	1987 1998 2009	
Mauritius	1990 2000 2011	1990 2000 2011	1990 2000 2011
Mexico	1970 1990 1995 2000 2010 2015	1990 1995 2000 2010 2015	1970 1990 1995 2000 2010 2015
Morocco	1982 1994 2004 2014	1982 1994 2004 2014	
Mozambique	1997 2007	1997 2007	
Nepal	2001 2011	2001 2011	2001 2011
Netherlands	1971 2001 2011	2001 2011	
Nicaragua	1971 1995 2005	1995 2005	
Palestine	1997 2007 2017		1997 2017
Panama	1970 1980 1990 2000 2010	1980 1990 2000 2010	1970 1980 1990 2000 2010
Paraguay	1972 1982 1992 2002	1982 1992 2002	1972 1982 1992 2002
Peru	1993 2007	1993 2007	1993 2007

Table A.1 Continued: Countries and years with APG data

Portugal	1981 1991 2001 2011	1981 1991 2001 2011	
Romania	1977 1992 2002 2011	1992 2002 2011	
Rwanda	2002 2012	2002 2012	2002 2012
Senegal	1988 2002 2013	1988 2002 2013	1988 2002 2013
South Africa	1996 2001 2007	1996 2001 2007	1996 2001 2007
Spain	1981 1991 2001 2011	1981 1991 2001 2011	
Switzerland	1970 1980 1990 2000	1980 1990 2000	
Tanzania	1988 2002 2012	1988 2002 2012	1988 2002 2012
Thailand	1970 1980 1990 2000	1980 1990 2000	1970 1980 1990 2000
Togo	1970 2010	2010	
Trinidad And Tobago	1980 1990 2000	1980 1990 2000	1980 1990 2000
Turkey	1985 1990 2000	1985 1990 2000	
Uganda	1991 2002 2014	1991 2002 2014	1991 2002 2014
United States	1970 1980 1990 2000 2005 2010 2015	1980 1990 2000 2005 2010 2015	
Uruguay	1975 1985 1996 2006	1985 1996 2006	
Venezuela	1981 1990 2001	1981 1990 2001	1981 1990 2001
Vietnam	1989 1999 2009	1989 1999 2009	
Zambia	1990 2000 2010	1990 2000 2010	1990 2000 2010

Note: The "Model" column refers to data points where we have both empirical and the estimated APG. The model was calibrated for countries that have the full set of calibration information and all years from 1980 to 2015.

A.1 Construction of Variables using IPUMS

To determine whether an individual is engaged in agricultural economic activity, we use primarily the harmonized employment and industry variables provided by IPUMS. In cases where IPUMS does not provide a harmonized employment variable for a particular survey, we refer to the original survey variables to establish the employment status. If such variables are absent or inadequate, we consider an individual to be employed if their industry is known.

However, there are instances where the harmonized variable for industry is either unavailable or has significant missing values for employed individuals. Given the requirement that the industry must be known for inclusion in the analysis, we make several efforts to impute or derive the industry information using alternative variables. The process is as follows:

1. **Attempt to use original, non-harmonized industry variables**: If these are available in the original survey but not harmonized by IPUMS, we use them to assign an industry classification.

2. **Use occupation variables for imputation**: If the original industry variable is not available, we use occupation variables to impute industry data.

3. **Exclusion of surveys**: If neither industry nor occupation data is available or usable for imputation, the survey is excluded from the analysis.

Additionally, in cases where the industry is unknown for more than 4 percent of employed individuals, we proceed with imputing the missing values using occupation variables, provided they are available. We do not impute industry values using occupation if such imputation would introduce inconsistencies within a country's dataset, or if using occupation would not sufficiently resolve the issue of missing industry data.

Imputing years of schooling can be challenging, as inconsistencies in the underlying data can arise. We rely on the harmonized years of schooling variable available in IPUMS for consistency, provided that we are confident that the imputation of schooling years is consistent across time and countries. This means we only use the variable if we believe that IPUMS' imputation methods do not overestimate or underestimate years of schooling for a biased subsample of the population. Of the 45 countries for which years of schooling is made available by IPUMS, we calculate average years of schooling by agriculture and non-agriculture for 32 countries.

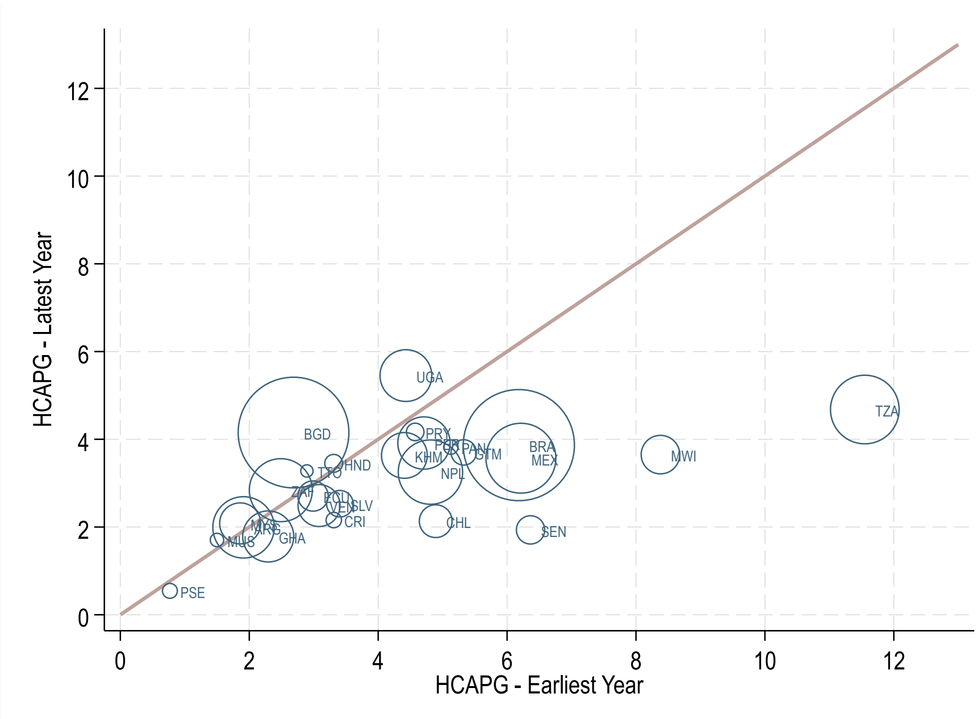
A.2 Human Capital Adjustment

The analysis presented in equation 1 does not account for differences in human capital per worker, which is a critical factor influencing productivity across sectors. Sectoral employment shares alone do not capture this dimension of productivity variation. To address this gap, we calculate a *Human Capital Adjusted Agricultural Productivity Gap* (HCAPG). Human capital is measured using years of schooling, with the assumption that the return to a year of schooling is consistent across countries, set at 10 percent based on standard values for the Mincerian returns to schooling.

The Human Capital Gap (HCG) is defined as:

$$HCG \equiv \frac{exp(0.1 \times \frac{S_n}{L_n})}{exp(0.1 \times \frac{S_a}{L_a})}, \tag{17}$$

Figure A.1: Change in HCAPG: Earliest vs Latest Years



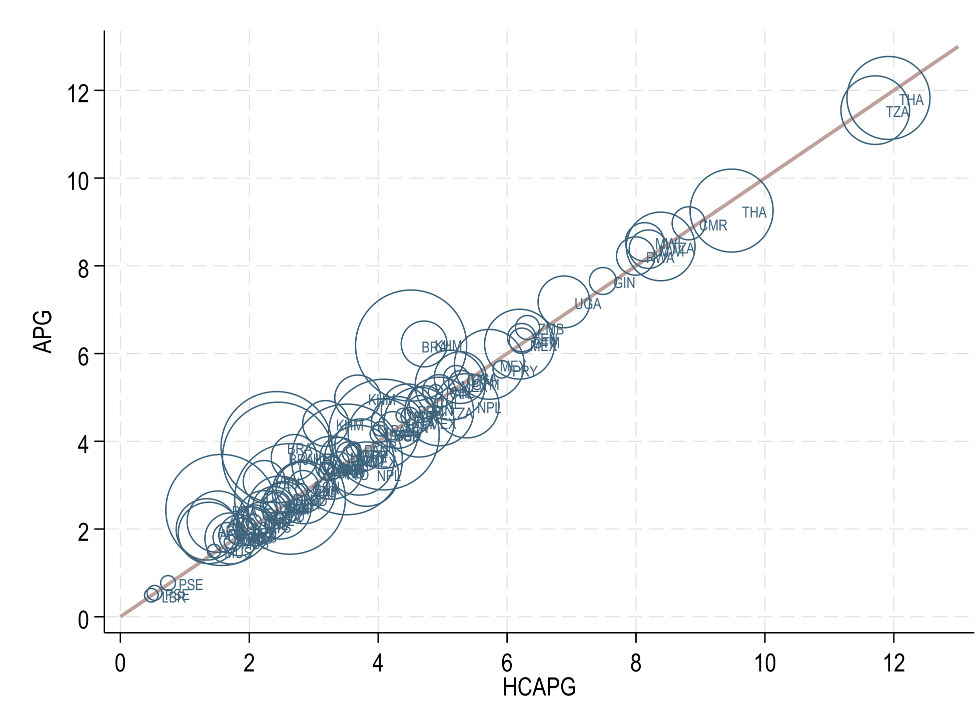
where S_n and S_a represent total years of schooling in non-agriculture and agriculture sectors, respectively, and L_n and L_a are the respective labor forces in these sectors.

The Human Capital Adjusted Agricultural Productivity Gap (HCAPG) is then calculated by dividing the original APG by the human capital gap:

$$\text{HCAPG} = \frac{APG}{HCG}. \tag{18}$$

We calculate the HCAPG for 32 countries, where information on education levels is available. As we can see in Figure A.2, the HCAPG makes a minimal difference to the APG for most country-year data points. Brazil and Cambodia are the only countries where the HCAPG is more than one unit lower than the APG. Figure A.2 shows that we still have an interesting mix of APG dynamics with some countries, like Brazil, seeing a decline in their APG while others, like Bangladesh, see an increase in their APG. We also continue to see a clustering of countries with stagnant APGs.

Figure A.2: APG vs HCAPG



B Additional Tables and Graphs

Figure B.1: Changes in APGs and Agricultural Shares of Employment (OECD Database)

Note: The graph plots the change in APG against the change in the agricultural employment share between each country's first and last observations over the 1980–2015 period, based on OECD data.

Table B.1: Log Changes in APGs, Model versus Data

		Model-generated Changes			
Country	Data Change	Baseline	Productivity Growth	Trade Costs	Labor Sectoral Move
ARG	-0.08	0.14	0.55	0.02	-0.43
AUT	0.12	0.09	0.68	-0.03	-0.51
BEN	-0.05	-0.23	-0.15	0.09	-0.17
BFA	-0.39	-0.27	0.34	-0.18	-0.46
BGD	0.44	-0.43	-0.23	0.01	-0.21
BOL	-0.39	0.66	0.84	0.02	-0.21
BRA	-0.38	-0.35	0.32	0.00	-0.70
CAN	0.26	0.60	0.89	0.06	-0.23
CHE	0.21	-0.44	-0.03	-0.01	-0.36
CHL	-0.88	-0.85	-0.52	0.02	-0.40
CHN	0.59	0.69	1.14	0.01	-0.47
CRI	-0.13	-0.34	0.24	0.02	-0.54
ECU	-0.10	-0.67	-0.15	0.04	-0.50

Table B.1 Continued: Changes in APGs

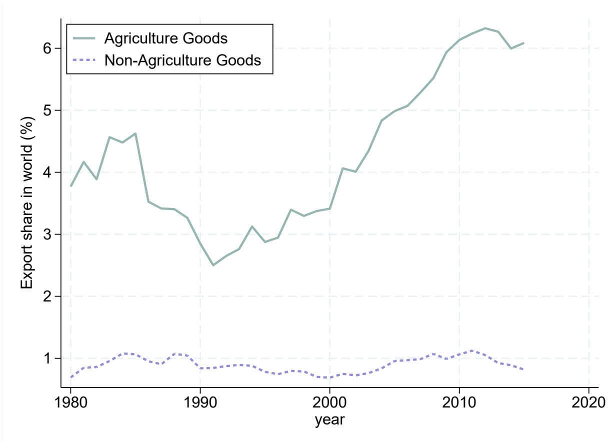
EGY	0.08	0.08	0.31	0.13	-0.39
ESP	-0.64	-0.45	0.19	0.00	-0.61
FJI	0.36	-0.48	0.09	0.04	-0.58
FRA	-0.12	0.14	0.48	0.01	-0.33
GHA	-0.25	-0.11	0.38	0.02	-0.50
GIN	-1.51	-1.58	-1.14	0.25	-0.71
GRC	-0.20	0.65	1.29	0.00	-0.64
GTM	-0.53	-0.76	-0.30	0.03	-0.46
HND	-0.03	-0.28	-0.10	0.05	-0.20
HTI	1.38	0.53	0.40	0.11	0.02
HUN	0.98	0.87	0.73	-0.05	0.21
IDN	-0.07	0.09	0.78	0.00	-0.71
IND	0.46	0.52	1.16	-0.01	-0.63
IRL	0.82	-0.12	0.56	-0.07	-0.55
ISR	-0.39	-0.29	0.05	-0.08	-0.28
JAM	-0.70	-0.68	-0.34	0.05	-0.35
KHM	-0.19	-0.01	0.15	0.06	-0.24
MAR	-0.49	-0.27	0.25	0.11	-0.63
MEX	-0.16	-0.26	0.23	0.04	-0.51
MLI	-0.32	0.27	0.73	0.03	-0.49
MOZ	-0.08	-0.17	0.07	-0.02	-0.23
MUS	0.13	1.23	1.47	0.02	-0.24
MWI	-0.83	-1.80	-1.37	0.03	-0.44
MYS	0.15	-0.44	-0.02	0.00	-0.39
NIC	-0.04	-0.24	-0.09	0.03	-0.18
NLD	-0.09	0.48	0.58	-0.03	-0.06
NPL	-0.39	0.57	0.84	0.02	-0.31
PAN	-0.18	-1.18	-0.72	0.02	-0.47
PER	-0.18	0.22	0.50	0.01	-0.30
PRT	0.13	0.28	0.86	0.00	-0.56
PRY	-0.30	-1.00	-0.66	0.07	-0.40
ROU	1.19	2.19	2.53	0.04	-0.33
RWA	-0.58	-1.07	-0.83	-0.12	-0.14
SEN	-1.19	-0.93	-0.57	0.15	-0.52
SLV	-0.30	0.80	1.13	0.03	-0.32
THA	0.43	-0.36	0.14	0.00	-0.49
TTO	0.12	-0.39	-0.09	0.04	-0.31
TUR	0.07	-0.24	0.14	-0.01	-0.35
TZA	-0.90	-1.08	-0.53	-0.03	-0.57

Table B.1 Continued: Changes in APGs

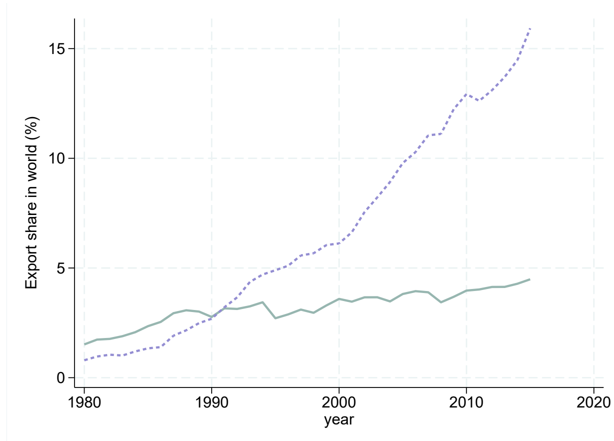
UGA	0.21	0.17	0.46	0.05	-0.35
URY	-0.22	0.46	0.71	-0.04	-0.23
USA	-0.18	-0.42	0.16	0.04	-0.50
VEN	-0.21	-0.97	-0.70	0.01	-0.30
VNM	0.22	0.91	0.90	0.17	-0.20
ZAF	0.13	0.32	0.35	0.10	-0.10
ZMB	0.88	0.59	0.98	-0.01	-0.40
Mean	-0.07	-0.09	0.27	0.02	-0.38
Slope		1.01	0.99	-0.01	0.03
Slope if data change≥0		1.36	1.47	-0.07	-0.05
Slope if data change<0		1.24	1.21	-0.02	0.07
Correlation		0.80	0.76	-0.13	0.09
Correlation if data change≥0		0.63	0.62	-0.33	-0.06
Correlation if data change<0		0.69	0.66	-0.10	0.10

Notes: The slope and correlation are calculated using each country's initial employment as weights.

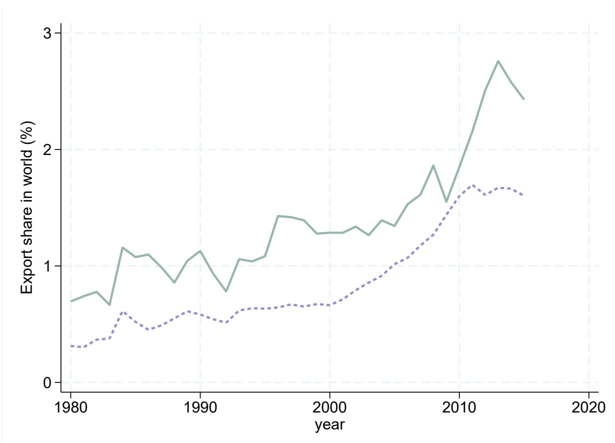
Figure B.2: Export Patterns across Countries



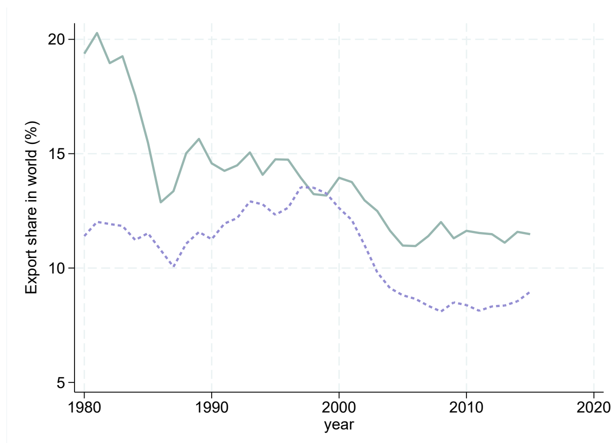
(a) Brazil



(b) China



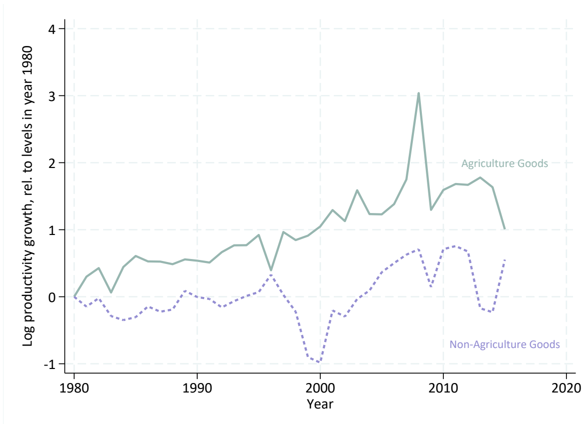
(c) India



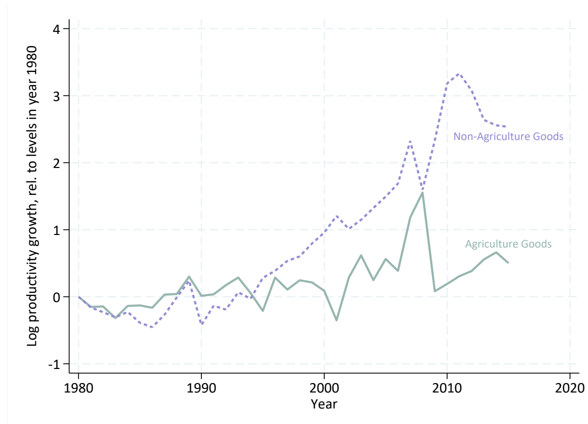
(d) United States

Note: The graphs show the country's exports as a percentage of the global total for each respective year and sector.

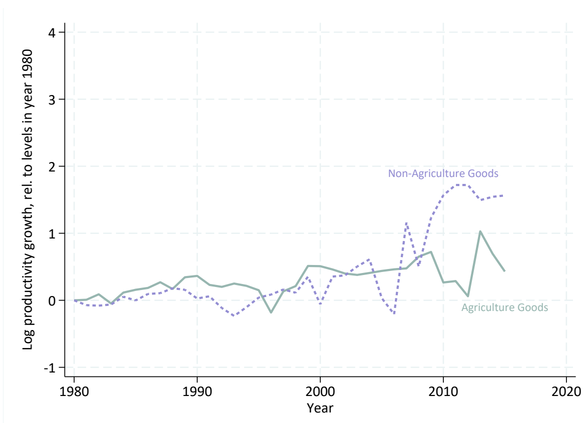
Figure B.3: Productivity Growth Relative to Year 1980



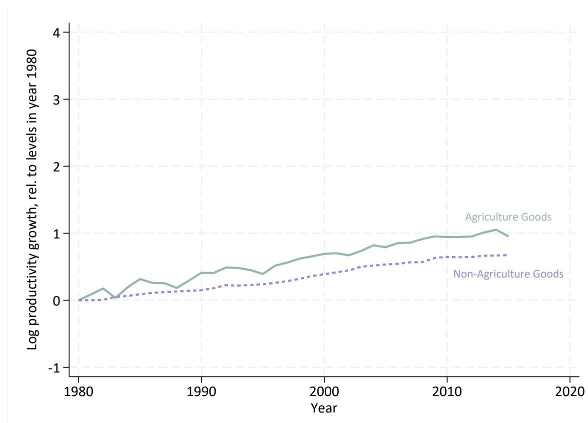
(a) Brazil



(b) China



(c) India



(d) United States

Figure B.4: Changes in Agricultural Employment Shares

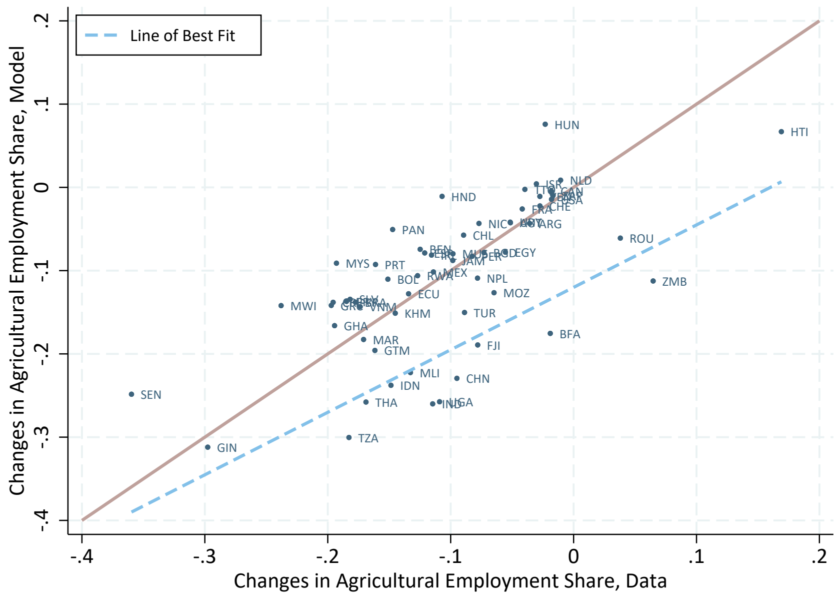
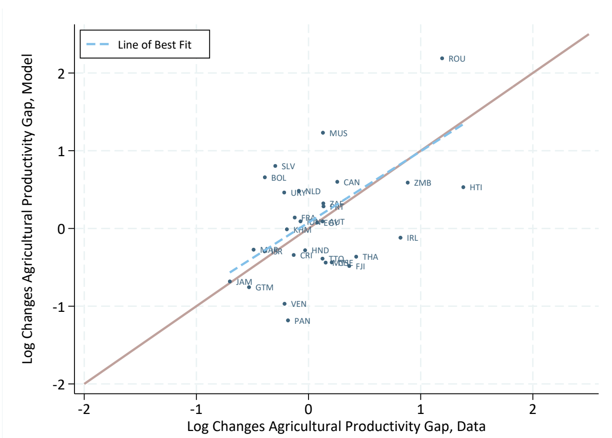
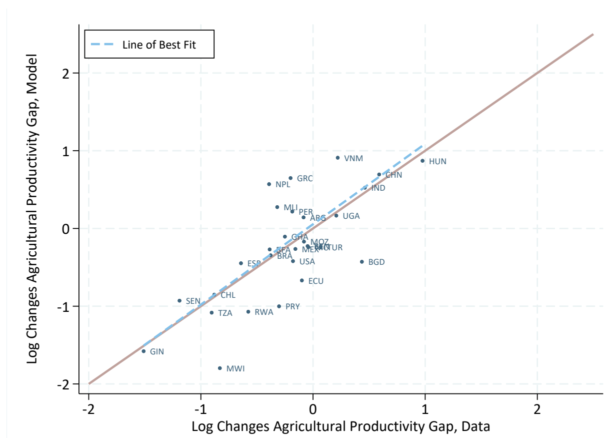


Figure B.5: Dynamics of APGs: Model vs Data



(a) More Open Countries



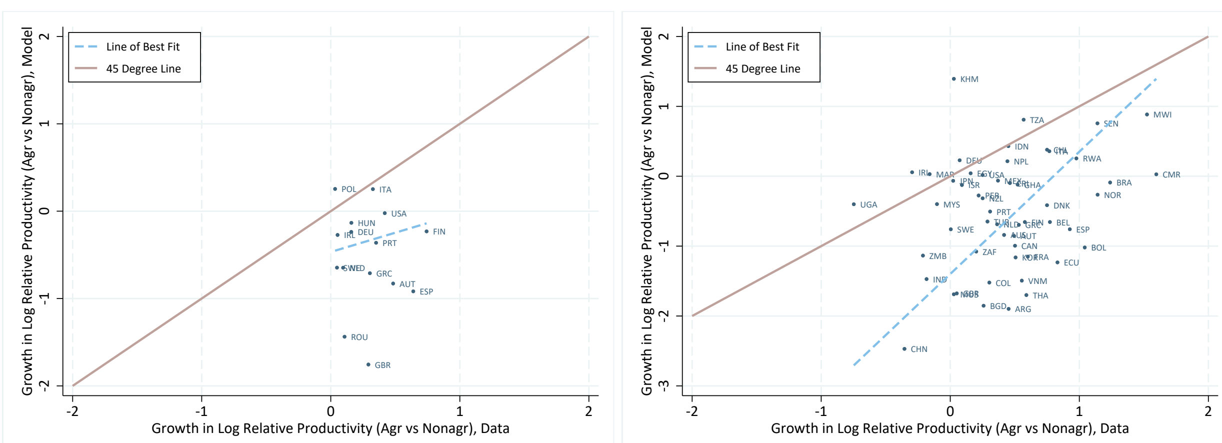
(b) Less Open Countries

Note: We measure the openness for each country by (Imports+Exports)/GDP for the first year of observation in the 1980–2015 period. Countries are categorized as either more open or less open based on whether their openness measure surpasses the median.

Figure B.6: Relative Prices of Agriculture across Countries

Note: We rely on the GGDC Productivity Level Database (Inklaar, Marapin, and Gräler, 2023), which presents data on relative prices and labor productivity across 84 countries and 12 sectors, for 2011. These data are largely based on the results of the 2011 International Comparisons Program (ICP). In the data, the price index of the U.S. is normalized to 1 in each year and sector. For ease of comparison, we perform the same normalization in each sector and year for the model-generated data.

Figure B.7: Comparison of Relative Productivity Growth between Data and Model Estimates



(a) EU KLEMS

(b) Data from Herrendorf et al. (2026)

Note: For each country, in the data, we compute the relative productivity growth between the first observation and the last observation during 1980–2015; in the model, we compute the productivity growth using the same time window as in the data.

Figure B.8: Changes in APGs, with Cobb-Douglas Preferences

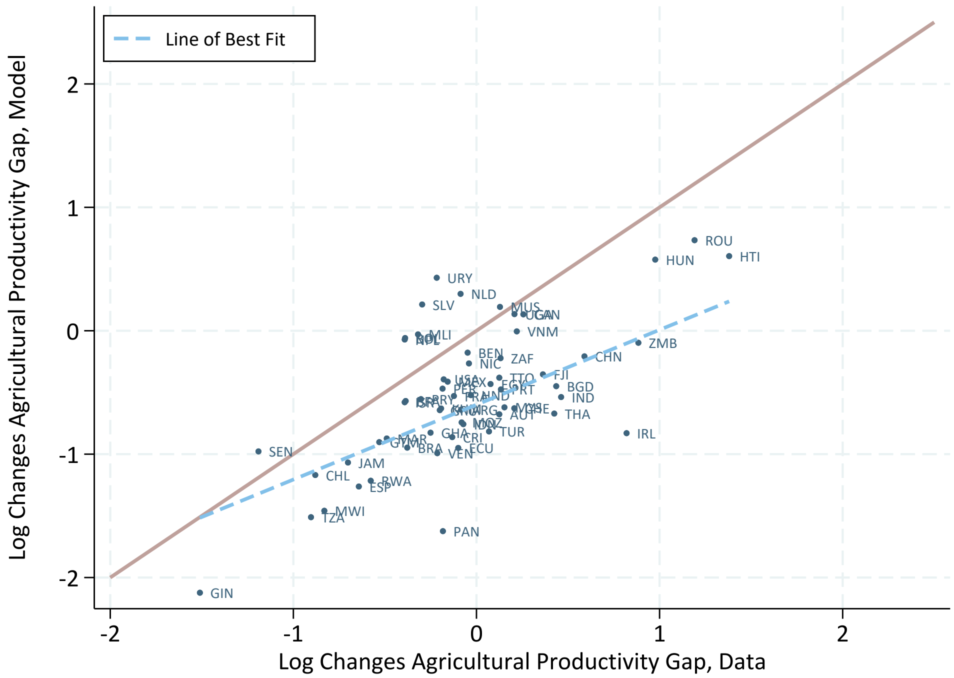
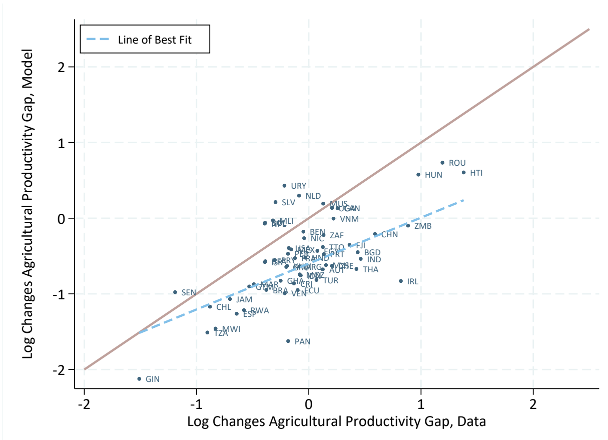
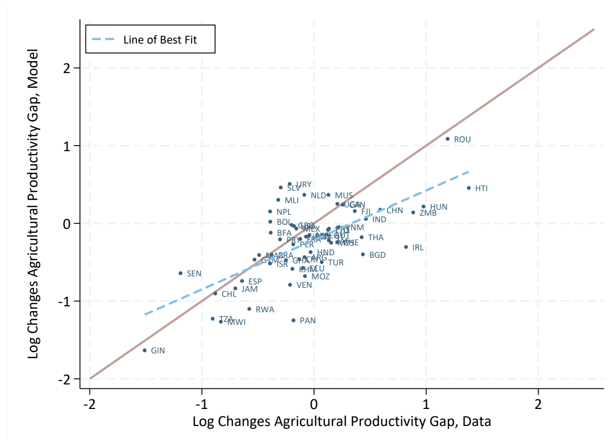


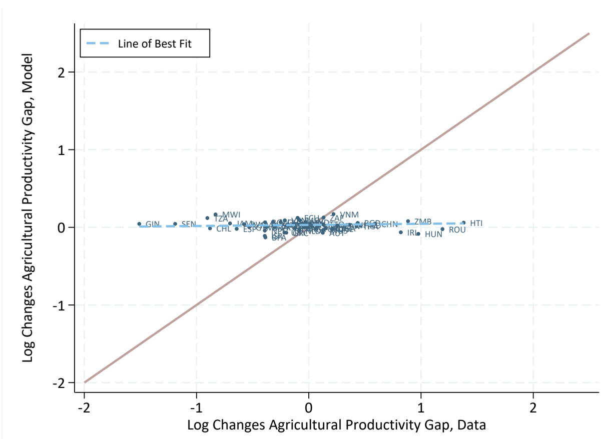
Figure B.9: Dynamics of APGs in Counterfactual Scenarios, with Cobb-Douglas Preferences



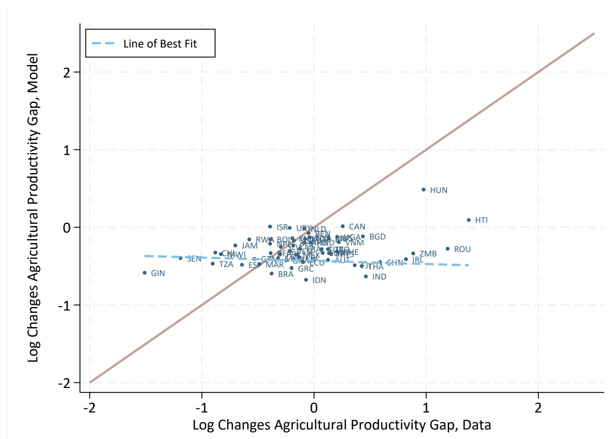
(a) Baseline Model



(b) Contribution of Productivity Growth

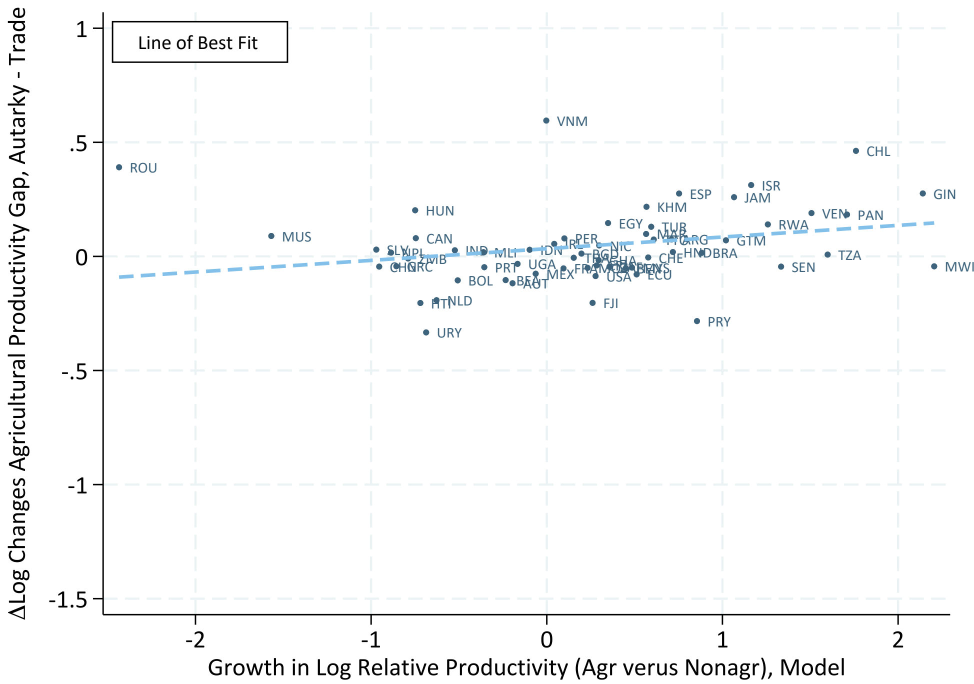


(c) Contribution of Changes in Trade Costs



(d) Contribution of Sectoral Labor Movements

Figure B.10: Dynamics of APGs, Autarky versus Baseline Model



Note: We plot the difference of combined effects of productivity growth and labor movements between the baseline and the autarkic scenarios against relative productivity growth between agriculture and non-agriculture during the same time window.

C Additional Quantitative Results

C.1 Countries Used in Calibration

The countries used in calibration include: Argentina; Australia; Austria; Bangladesh; Belgium-Luxembourg; Benin; Bolivia; Brazil; Burkina Faso; Cambodia; Cameroon; Canada; Chile; China; Colombia; Costa Rica; Denmark; Ecuador; Egypt; El Salvador; Fiji; Finland; France; Germany; Ghana; Greece; Guatemala; Guinea; Haiti; Honduras; Hungary; Iceland; India; Indonesia; Ireland; Israel; Italy; Jamaica; Japan; Liberia; Malawi; Malaysia; Mali; Mauritius; Mexico; Morocco; Mozambique; Nepal; Netherlands; New Zealand; Nicaragua; Norway; Panama; Paraguay; Peru; Poland; Portugal; Rest of World; Republic of Korea; Romania; Rwanda; Senegal; South Africa; Spain; Sweden; Switzerland; Tanzania; Thailand; Togo; Trinidad And Tobago; Turkey; Uganda; United Kingdom; United States; Uruguay; Venezuela; Vietnam; and Zambia.

C.2 Decomposition of Dynamics into Relative Price and Productivity Effects

According to equation (12), our model has a simple decomposition of APGs:

$$APG = \frac{w_i^n}{w_i^a} = \underbrace{\frac{w_i^n/z_i^n}{w_i^a/z_i^a}}_{\text{relative price of non-agriculture}} \times \underbrace{\frac{z_i^n}{z_i^a}}_{\text{relative productivity of non-agriculture}}.$$

As we consider perfect competition, marginal costs equal prices for each sector. Thus, the first component in this decomposition, $\frac{w_i^n/z_i^n}{w_i^a/z_i^a}$, captures relative prices of nonagricultural versus agricultural goods. In our model, the relative prices are determined by the demand and supply of goods in each sector, which are affected by all of our three channels (productivity growth, trade, and barriers to labor movements). The second component, z_i^n/z_i^a, captures the relative productivity of non-agricultural versus agricultural goods, which directly relates to the productivity channel we studied.

To understand the relative contributions of price changes and productivity growth to the dynamics of APGs, we perform the following regression using the model-generated data:

$$y_i = \beta_0 + \beta_1 \Delta \log APG_i + \varepsilon_i,$$

where $\Delta \log APG_i$ is the model-generated changes in APGs, using the same time window for each country as in Figure 6. We separately use changes in log relative prices and changes in log relative productivity as the dependent variable. In this specification, the coefficients from these two regressions shall add up to 1.

Table C.1: Relative Contributions of Price Changes and Productivity Growth

Dep var	log rel prices	log rel productivity	log rel prices	log rel productivity
	(1)	(2)	(3)	(4)
	unweighted	unweighted	weighted	weighted
log APG	-0.185***	1.185***	-0.262**	1.262***
	(0.0527)	(0.0527)	(0.117)	(0.117)
Obs	59	59	59	59
R-squared	0.138	0.868	0.180	0.836

Notes: Regressions in Columns (1)–(2) are unweighted, whereas regressions in Columns (3)–(4) are weighted by employment in each country in the initial year of observation. Robust standard errors are in parentheses. Significant levels: * 10%, ** 5%, *** 1%.

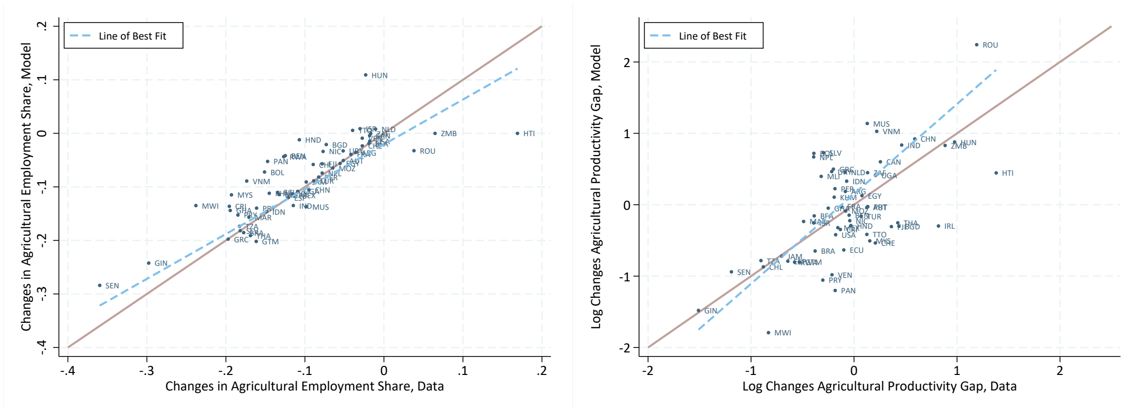
Table C.1 shows that, according to this decomposition, relative productivity growth between non-agriculture and agriculture is the primary driver of the dynamics of APGs. It is worth noting that this decomposition is based on model estimates. Due to the lack of long time series on both prices and productivity, we are unable to directly perform the decomposition with the observed data. However, relying on the GGDC Productivity Level Database, which provides data on relative prices based on the 2011 International Comparisons Program (ICP), we observe that the model-generated relative price of agriculture aligns reasonably well with the data, as shown in Figure B.6. We will also show that the model's estimates for sectoral productivity growth align well with the data in Section B.

C.3 Country-specific Chances of Switching Sectors

In our baseline model, we assume the chances of switching sectors to be identical across countries. Given that labor movements from agriculture to non-agriculture could be an important "push" factor for APG changes, here we utilize a country-specific proportion of workers with opportunities to switch sector. Specifically, for each country i, we choose the opportunity to switch sectors κ_i, according to the average change in the share of agricultural employment in that country over the 1980–2015 period. We keep all our parameters unchanged from the baseline calibration.

Panel (a) of Figure C.1 shows that this extended model matches the observed changes in agricultural employment better than the baseline model (Figure B.4). Panel (b) of Figure C.1 shows

Figure C.1: Quantitative Results with Country-Specific Opportunities for Sector Switching



(a) Changes in Agricultural Employment Shares

(b) Dynamics of APGs

Notes: We utilize a country-specific proportion of workers with opportunities to switch sectors, based on the average proportional change in agricultural employment shares over the years for each country. All other parameters remain unchanged from the baseline model. The regression is weighted by each country's initial employment.

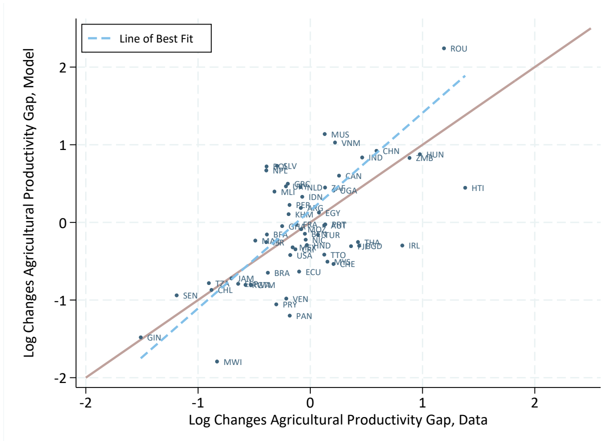
that the prediction on APG dynamics remains largely unchanged from the baseline (Figure 5).

Figure C.2 illustrates the contributions of productivity growth, trade costs, and labor sectoral movements. While the effects of productivity growth and trade costs remain similar to the baseline, the role of labor sectoral movements strengthens: the slope of APG growth driven by labor mobility on the observed APG changes rises from 0.03 to 0.29 when allowing country-specific sector-switching opportunities. As a result, the share of variance in observed APG dynamics explained by the three channels increases from 63.4 percent in the baseline (Table 2) to 69.4 percent. Nonetheless, sectoral productivity growth continues to be the primary driver of cross-country variation in APG growth.

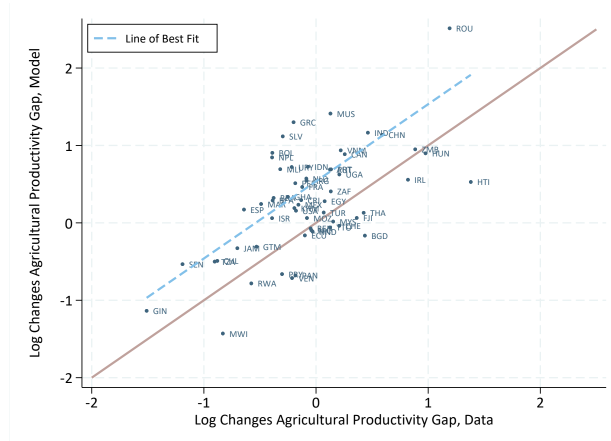
C.4 Using Price and Wage Data to Recover Productivity Levels

In equation (13), only relative S_{it}^{j} matters, and therefore we can only estimate S_{it}^{j} relative to a reference country (and thus lack one degree of freedom for each year and sector). In the baseline calibration, we resolved this issue by choosing the U.S. as the reference country and directly employing sectoral growth data of output per worker from FRED and USDA to measure the U.S. sectoral productivity levels. We notice that a large literature also uses price data in the estimation process to recover productivity levels for the U.S. (e.g., Herrendorf, Herrington, and Valentinyi, 2015). To apply price data in our estimation process, after estimating equation (13) and obtaining

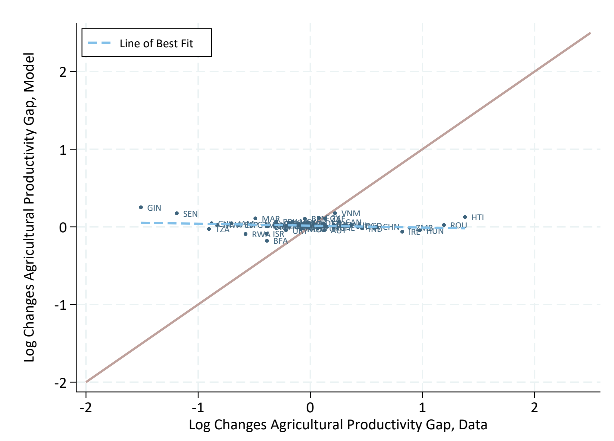
Figure C.2: Dynamics of APGs in Counterfactual Scenarios (country-specific switching chances)



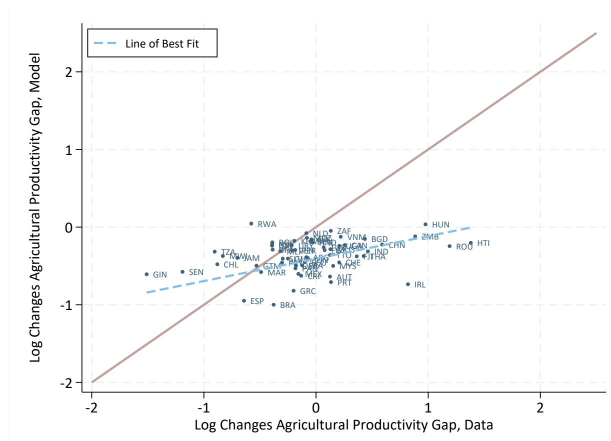
(a) Baseline



(b) Contribution of Productivity Growth



(c) Contribution of Changes in Trade Costs



(d) Contribution of Sectoral Labor Movements

the estimates relative to the U.S. level ($\hat{S}_{it} - \hat{S}_{USt}$), we note from equation (8) that:
(19)

$$\hat{p}^j_{USt} = \left[\sum_k \exp(\hat{S}^j_{kt})(\hat{d}^j_{kUSt})^{1-\eta}\right]^{1/(1-\eta)} = \left[\sum_k \exp(\hat{S}^j_{USt})\exp(\hat{S}^j_{kt} - \hat{S}^j_{USt})(\hat{d}^j_{kUSt})^{1-\eta}\right]^{1/(1-\eta)}.$$

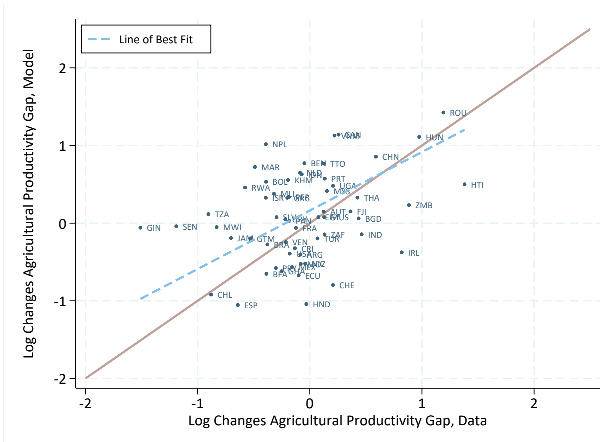
Thus, we use the U.S. price data $\hat{p}^j_{USt}$ for each year and sector to recover $\hat{S}^j_{USt}$ and other countries' estimates $\hat{S}^j_{it}$. We extract data on the U.S. price indices from the EU KLEMS database (The Conference Board, 2023).

We then proceed with two approaches to calibrate sectoral productivity levels z^j_{kt} for the U.S. and other countries.

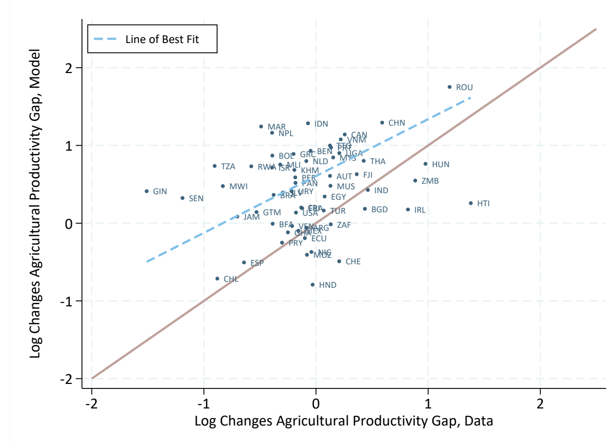
1. **Method of Moments.** We employ a similar approach as in our baseline calibration. Specifically, we search for the set of productivity levels $\{z^j_{kt}\}$ in the model that minimize the summed absolute difference between the model-predicted "competitiveness" level $\{S^{j,model}_{it}\}$ and the model estimates $\{\hat{S}^j_{it}\}$, $\sum_t \sum_i \sum_j |\hat{S}^j_{it} - S^{j,model}_{it}|$. Since we used price data from the U.S. to determine the absolute level of S^j_{it}, there is no longer a need for a reference country. This allows us to estimate productivity levels for each country and sector, aligning them with the levels of S^j_{it} through this estimation process.

   Figure C.3 shows that with the productivity levels estimated using price data, the model predictions align well with the observed changes in APGs.

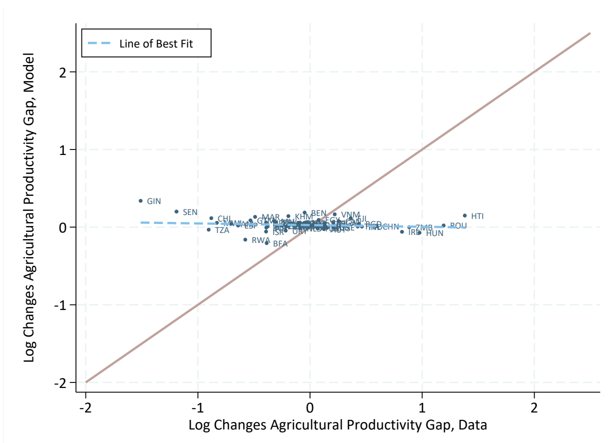
Figure C.3: Dynamics of APGs in Counterfactual Scenarios (alternative calibration based on price data)



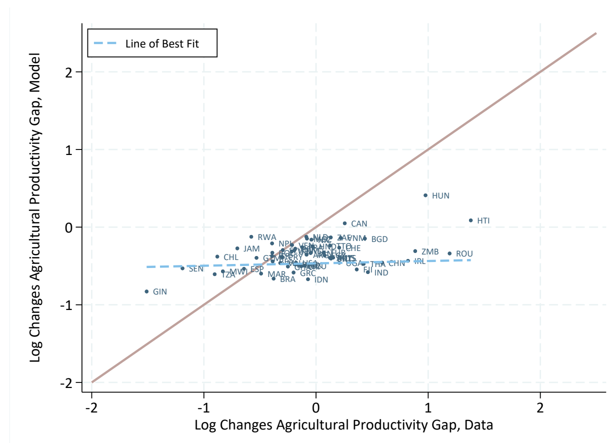
(a) Baseline



(b) Contribution of Productivity Growth



(c) Contribution of Changes in Trade Costs



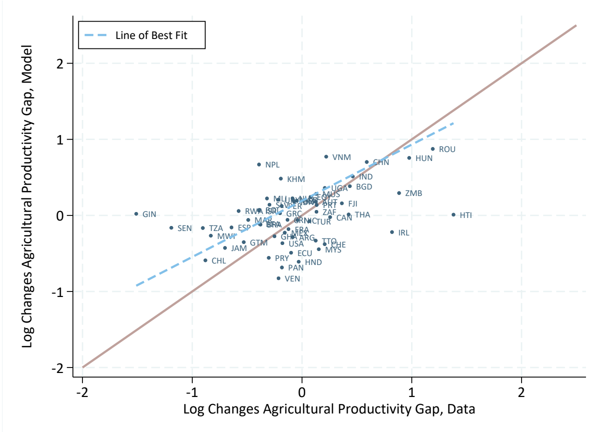
(d) Contribution of Sectoral Labor Movements

2. **Using Wage Data.** Recall that $S_{kt}^{j} = (1-\eta)(\log w_{kt}^{j} - \log z_{kt}^{j})$. We note from the expression of marginal costs that:

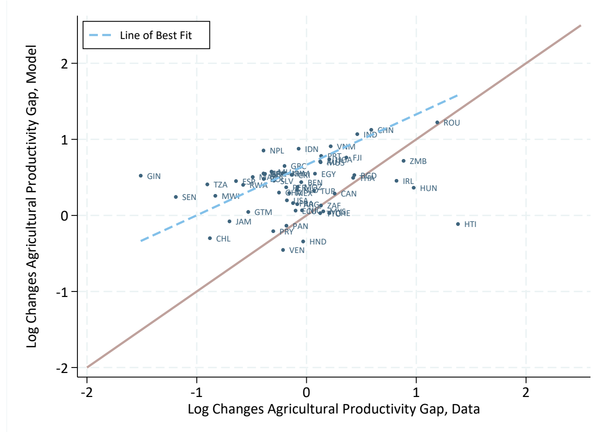
$$S_{it}^{a} = (1-\eta)\left[\log w_{it}^{a} - \log z_{it}^{a}\right]; \quad S_{it}^{n} = (1-\eta)\left[\log w_{it}^{n} - \log z_{it}^{n}\right]$$

To recover productivity estimates $\hat{z}_{it}^{j}$ from the estimates $\hat{S}_{it}^{j}$, we require yearly sectoral wage rates w_{kt}^{j}. To avoid directly incorporating the dynamics of APGs in the calibration, for each country, we first use sectoral value added per worker to compute sectoral wage rates in the initial year (1980). We then combine these initial values with the yearly growth of GDP per capita (common to two sectors) to construct sectoral wage rates in later years.

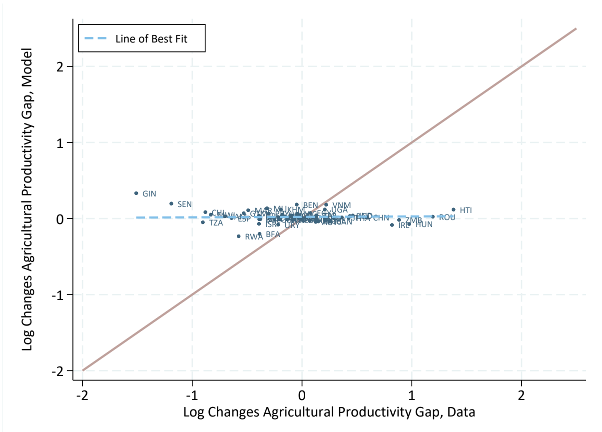
Figure C.4: Model Fit of Dynamics of APGs (alternative calibration based on price and wage data)



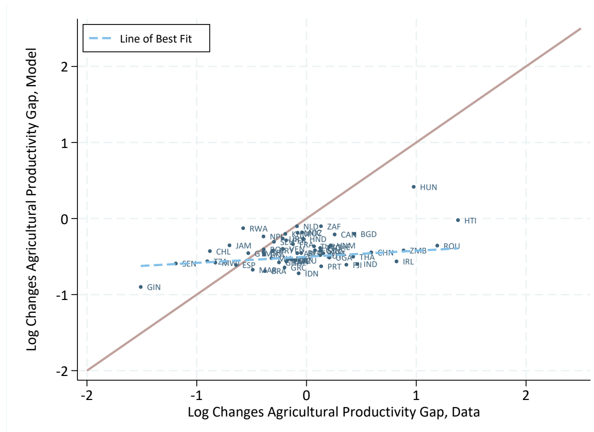
(a) Baseline Model



(b) Contribution of Productivity Growth



(c) Contribution of Changes in Trade Costs



(d) Contribution of Sectoral Labor Movements

Figure C.4 shows that with the productivity levels estimated using price and wage data, the model predictions still align well with the observed changes in APGs.

C.5 Alternative Functional Form of Indirect Utility

Alternatively, we can use the indirect utility from Boppart (2014) in the case of two goods:

$$V_i(w) = \frac{1}{\varepsilon}\left(\frac{w}{p_i^n}\right)^{\varepsilon} - \frac{\nu}{\gamma}\left(\frac{p_i^a}{p_i^n}\right)^{\gamma} - \frac{1}{\varepsilon} + \frac{\nu}{\gamma},$$

with $1 > \gamma > 0$, $1 > \varepsilon > 0$, and $v > 0$. This implies a share of expenditures on agricultural goods:

$$\vartheta_i(w) = v\left(\frac{p_i^n}{w}\right)^{\varepsilon}\left(\frac{p_i^a}{p_i^n}\right)^{\gamma}.$$

The elasticity of substitution between two goods are given by:

$$\rho = 1-\gamma - \frac{v\left(\frac{p_i^a}{p_i^n}\right)^{\gamma}}{\left(\frac{w}{p_i^n}\right)^{\varepsilon} - v\left(\frac{p_i^a}{p_i^n}\right)^{\gamma}}(\gamma-\varepsilon),$$

which, depending on the values of γ, ε, and v, does not necessarily exceed 1. The elasticity of substitution converges to $1-\gamma$ when income w goes to infinity.

To estimate ε and γ, we perform the following regression:

$$\log\vartheta_{it} = \beta_0 + \varepsilon\log(p_{it}^n/w_{it}) + \gamma\log(p_{it}^a/p_{it}^n) + \varepsilon_{it} \quad (20)$$

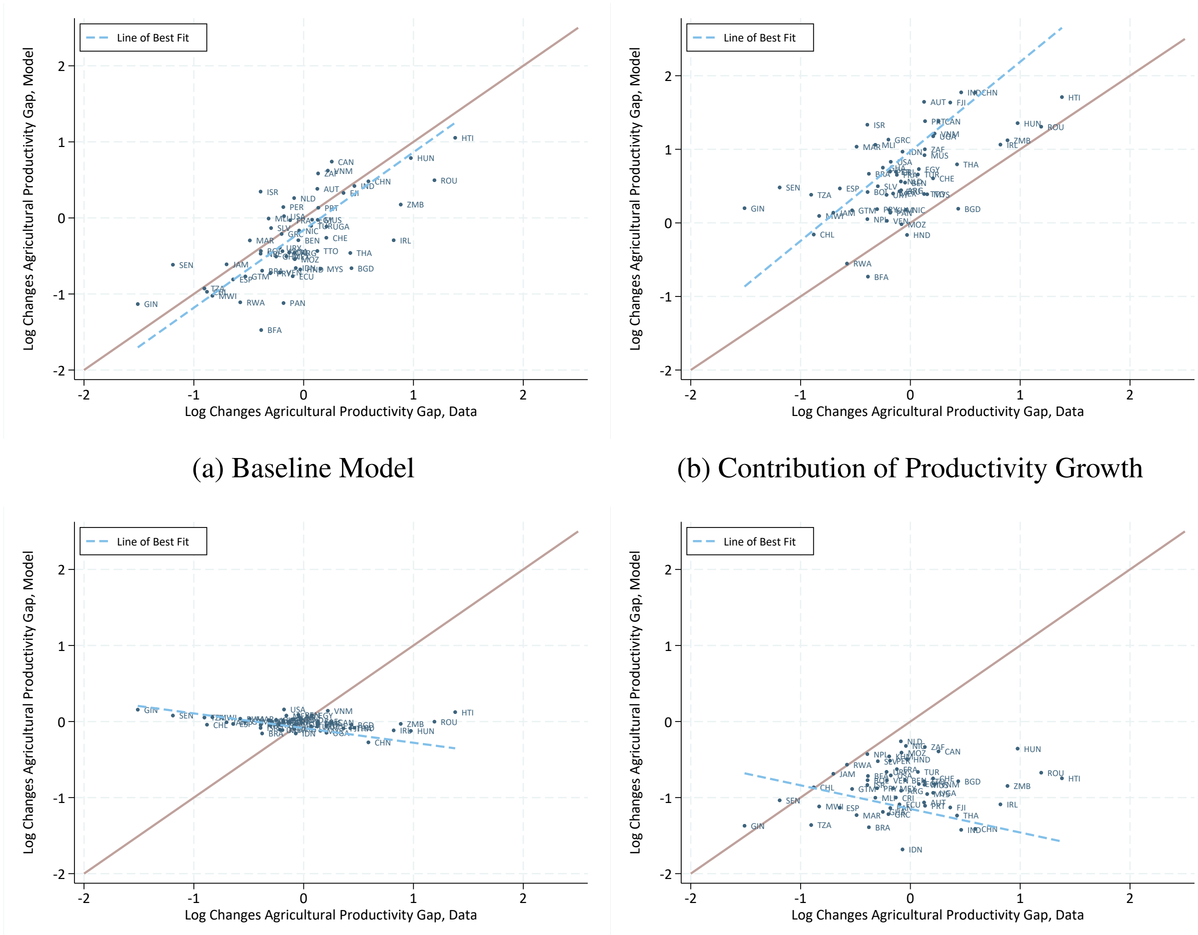
We calculate the share of expenditures on agricultural goods for each country and year using our sectoral value-added and trade data. We use GDP per employee for w_{it}. We estimate country-year-level price index by $\hat{p}_{it}^j = \left[\sum_k \exp(\hat{S}_{USt}^j)\exp(\hat{S}_{kt}^j - \hat{S}_{USt}^j)(\hat{d}_{kit}^j)^{1-\eta}\right]^{1/(1-\eta)}$, where $\hat{S}_{USt}^j$ represents the fixed effects for the U.S., obtained from matching the U.S. price level according to equation (19).

We conduct the regression analysis and find $\hat{\varepsilon} = 0.66$ and $\hat{\gamma} = 0.44$.[8] The estimate $\hat{\varepsilon} = 0.66$ corresponds to an income elasticity of agricultural consumption of 0.34, which is close to the 0.35 estimate reported in Boppart et al. (2023). This suggests that Engel curves for agricultural goods are flatter compared to those for non-agricultural goods. Additionally, $\hat{\gamma} > 0$ indicates that the two sectoral goods are gross complements. Finally, aligning with our baseline calibration, we still select the value of v to align with the APG for the U.S. at the beginning of our sample period, resulting in $v = 0.023$, as well as calibrating the productivity levels using the method of moments as described in Section B.

Figure C.5 shows that with the alternative version of indirect utility function (the calibration for the parameters of other model elements remain unchanged), the model predictions still align well with the observed changes in APGs.

[8] To avoid bias from interpolation, we conduct the regression analysis using only the country-years with actual APG data on agricultural shares of GDP and employment. The regression coefficients obtained from the full sample with interpolated data are quite similar.

Figure C.5: Model Fit of Dynamics of APGs (alternative functional form of indirect utility)



(a) Baseline Model

(b) Contribution of Productivity Growth

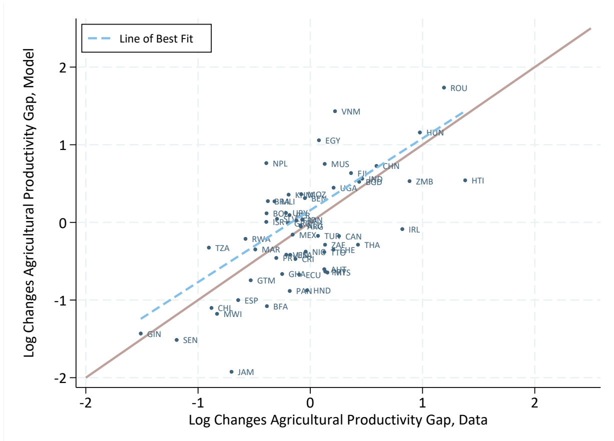
(c) Contribution of Changes in Trade Costs

(d) Contribution of Sectoral Labor Movements

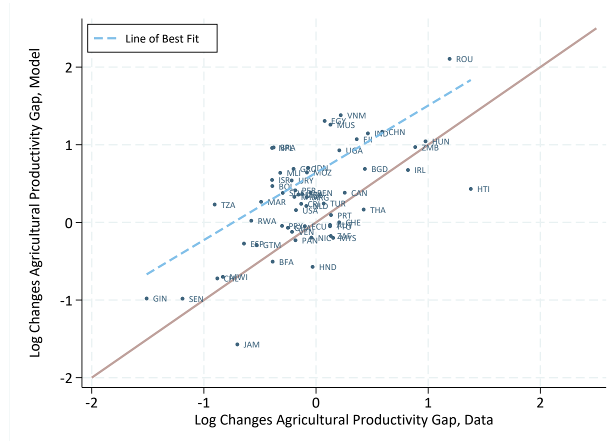
C.6 Restricted Sample

In our baseline calibration, we incorporated OECD data to better capture global trade networks, since the APG country list omits several major economies such as Canada, Germany, Japan, and the United Kingdom. To assess robustness, we exclude additional countries from the OECD database—while retaining those appearing in both the APG and OECD datasets, such as the United States—resulting in a sample of 62 countries plus a "Rest of World." We then recalibrate the model using this restricted sample and following the same steps in Section III. As shown in Figure C.6, the quantitative results remain largely consistent with the baseline.

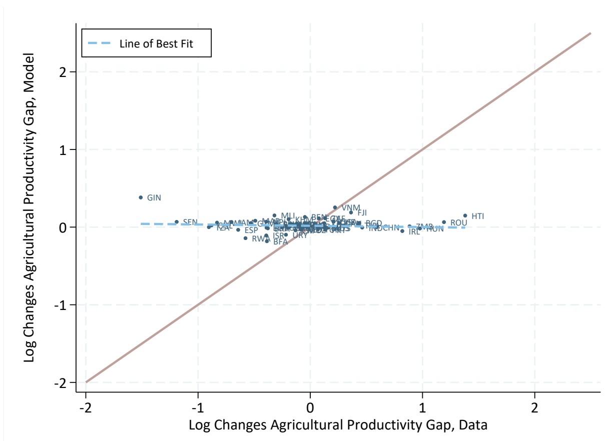
Figure C.6: Dynamics of APGs in Counterfactual Scenarios, Restricted Sample



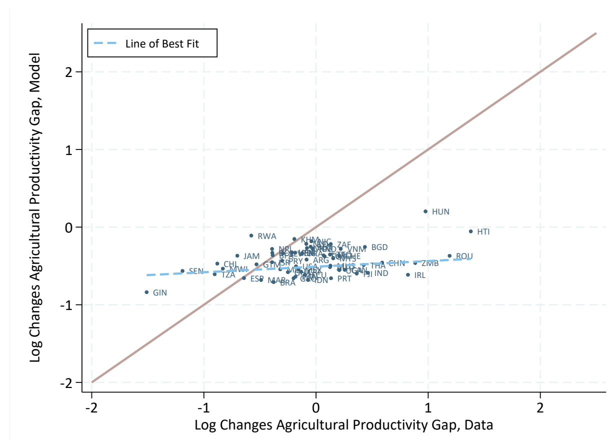
(a) Baseline Model



(b) Contribution of Productivity Growth



(c) Contribution of Changes in Trade Costs



(d) Contribution of Sectoral Labor Movements

C.7 Using Productivity Data from Herrendorf et al. (2026)

In our baseline calibration, productivity was inferred from international trade data. To assess robustness, we instead use directly measured sectoral labor productivity (in PPPs) over the 1990–2015 period from Herrendorf et al. (2026). Due to data constraints in this exercise, we restrict the sample to 53 countries rather than 77 and focus on the shorter 1990–2015 period instead of 1980–2015. Aside from using their productivity estimates rather than those derived from gravity estimation, we calibrate all other parameters—including trade costs and the probability of switching sectors—using the same procedure as in our baseline calibration.

Figure C.7 shows that the model-generated APG dynamics continue to match the data closely, much like in the baseline model. This alignment reflects the strong correspondence between our estimated productivity growth rates and those in Herrendorf et al. (2026) (Figure 8), since cross-country variation in APG dynamics is largely driven by productivity growth. For certain countries, such as China, the model-generated APG dynamics are somewhat lower than under the baseline productivity estimates, partly due to Herrendorf et al. (2026)'s underestimation of productivity growth for these economies.

Nonetheless, using the productivity estimates from Herrendorf et al. (2026) results in a poorer fit for the levels of APGs in the data (compared to the baseline model), as shown in Figure C.8. This pattern is consistent with the time-series patterns of APGs for four selected countries shown in the body of the paper. In particular, the model with productivity estimates from Herrendorf et al. (2026) predicts APGs of 9.7, 17.3, and 16.2 for Brazil, China, and India in 1990, whereas the corresponding data estimates are 2.4, 6.8, and 3.7. This discrepancy arises mainly because Herrendorf et al. (2026) report relatively higher levels of nonagricultural productivity than those implied by our model, particularly for poorer countries, as illustrated in Figure C.9.

C.8 Using Expenditure Share to Infer Productivity Growth

In the baseline model, we adopted an open-economy framework, which enabled us to use the gravity equation to infer productivity growth. We now turn to the closed-economy case, where $d_{ki}^j \to \infty$ for all $k \neq i$. In this setting, sectoral prices are given by $p_i^a = w_i^a/z_i^a$ and $p_i^n = w_i^n/z_i^n$. The system of equilibrium conditions for each country and year can then be expressed as:

$$\text{market clearing in agriculture}: \frac{\sum_j \vartheta_i(w_i^j) w_i^j l_i^j}{w_i^a/z_i^a} = z_i^a l_i^a,$$

$$\text{market clearing in non-agriculture}: \frac{\sum_j [1-\vartheta_i(w_i^j)] w_i^j l_i^j}{w_i^n/z_i^n} = z_i^n l_i^n,$$

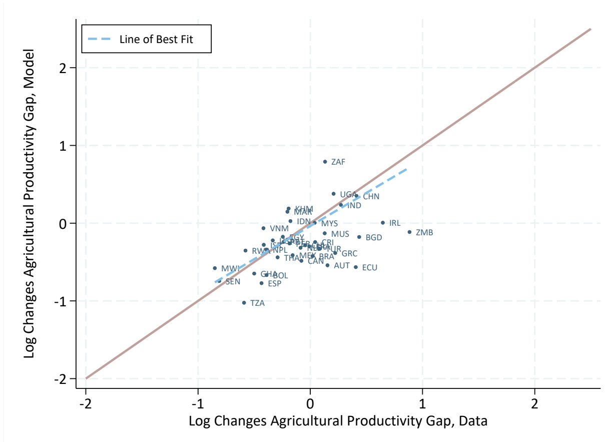
where the agricultural expenditure share, conditional on wage w, is given by

$$\vartheta_i(w) = \phi + \nu \left(\frac{w}{(w_i^a/z_i^a)^{\phi} (w_i^n/z_i^n)^{1-\phi}} \right)^{-\zeta}.$$

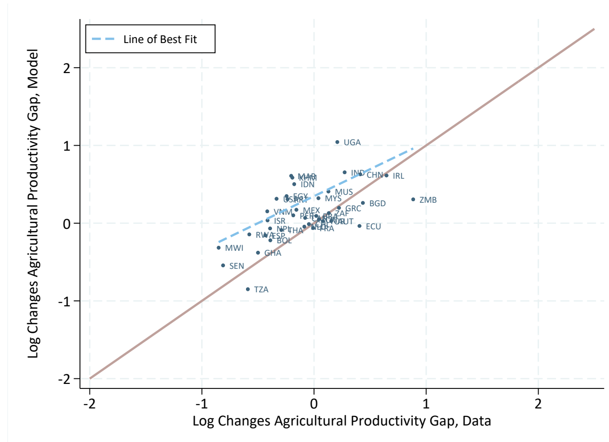
In this system, the left-hand side of each equation represents the demand for sectoral goods, while the right-hand side corresponds to their total supply. Given sectoral labor allocation and the parameters of the utility function,[9] we can solve for the two unknowns $\{w_i^a, w_i^n\}$ up to a normalization

[9] Labor allocation is determined by the initial employment shares at the beginning of the period and by the fraction of workers who can move to maximize their income. We keep the parameters of the utility function at their baseline

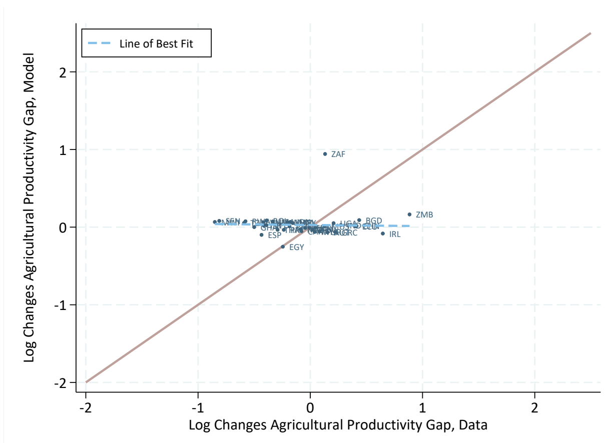
Figure C.7: Dynamics of APGs in Counterfactual Scenarios, Using Productivity from Herrendorf et al. (2026)



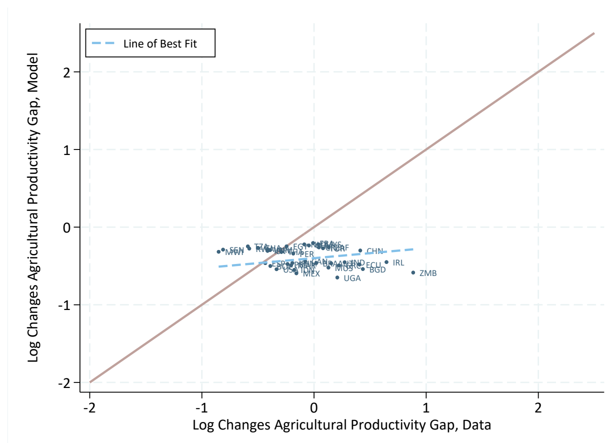
(a) Baseline Model



(b) Contribution of Productivity Growth



(c) Contribution of Changes in Trade Costs



(d) Contribution of Sectoral Labor Movements

from this pair of equations, conditional on a given set of productivity levels $\{z_i^a, z_i^n\}$.

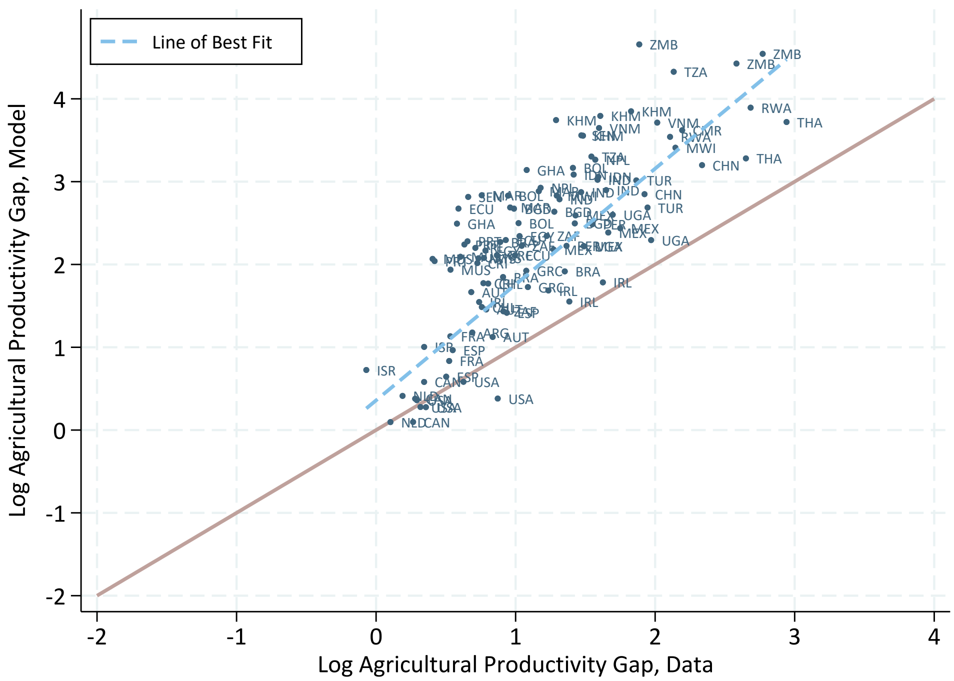
We infer $\{z_i^a, z_i^n\}$ using two data moments. The first is the country–year agricultural expenditure share. In the model, this is given by

$$\bar{\vartheta}_i = \frac{\sum_j \vartheta_i(w_i^j) l_i^j w_i^j}{\sum_j l_i^j w_i^j},$$

which depends on the productivity levels $\{z_i^a, z_i^n\}$, since these determine equilibrium wages and the corresponding expenditure shares. In the data, we construct this moment from sectoral value

calibration values.

Figure C.8: Levels of APGs: Model vs Data, Using Productivity from Herrendorf et al. (2026)



added and trade data for each country and year.[10]

The second moment is real GDP per capita (in PPP terms), normalized by the U.S. level in 1980. Because real GDP per capita is calculated using price levels in the base year—and PPP prices largely reflect prices in rich countries (Hsieh and Klenow, 2007)—we use U.S. sectoral prices in the initial year (1980) to proxy PPP prices and compute model-implied real GDP per capita as

$$GDPPC = \frac{\sum_j P^j_{US,t_0} l^j_i z^j_i}{\sum_j l^j_i},$$

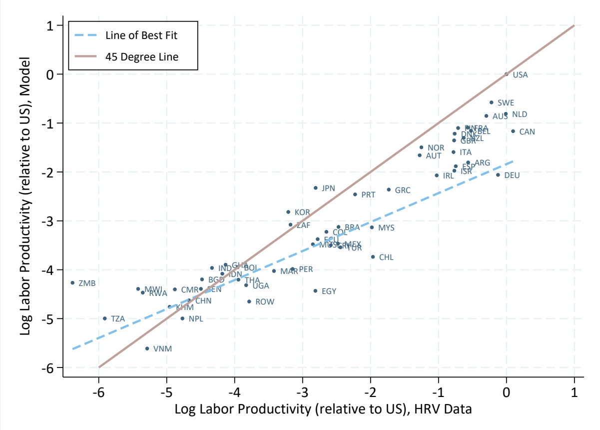
where P^j_{US,t_0} is obtained from the model equilibrium for the U.S. in 1980. Thus, the constructed GDP per capita is a function of $\{z^a_i, z^n_i\}$. In the data, we use the Penn World Table to measure each country–year's real GDP per capita (in PPP terms), normalized by the U.S. level in 1980.[11]

Using these two moments, we recover $\{z^a_i, z^n_i\}$ for each country–year via the method of mo-

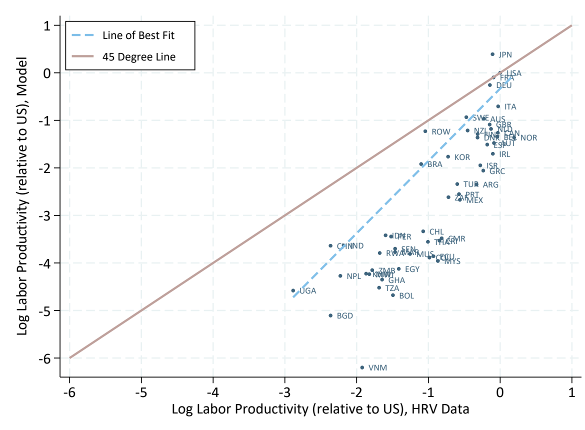
[10] If the agricultural expenditure share is negative due to measurement error or data noise, we supplement the value using the OECD Inter-Country Input-Output Tables (OECD, 2023).

[11] Since we normalize GDP per capita by the U.S. level in 1980, we do not have an independent data point for the U.S. in that year (as its GDP per capita is always 1 by definition). Therefore, we assume equal sectoral productivity for the United States in this initial year.

Figure C.9: Sectoral Productivity Levels in 1990 in the Model and Herrendorf et al. (2026)



(a) Agriculture



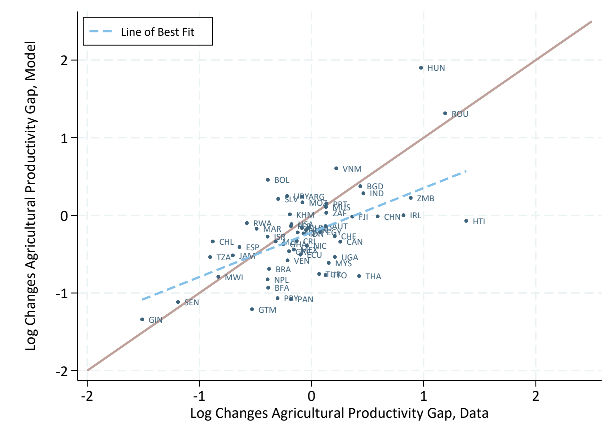
(b) Non-agriculture

ments. Combined with the parameter κ (the probability that workers switch sectors) from the baseline calibration—and noting that trade is absent in the closed-economy setting—we can conduct quantitative analyses to examine the dynamics of APGs.

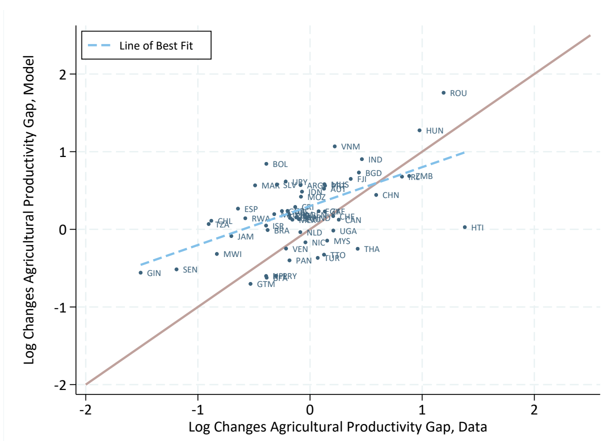
As illustrated in Figure C.10, the model continues to account for part of the observed APG dynamics. In economies with little trade, expenditure shares closely track output shares, implying that the APG corresponds to the ratio of relative expenditure shares to relative employment shares between non-agriculture and agriculture. Since our calibration targets expenditure shares and takes initial employment shares directly from the data (which evolve slowly due to mobility frictions), this procedure mechanically captures a portion of the APG dynamics.

However, for countries that are major exporters in specific sectors, sectoral expenditure shares tend to be smaller than output shares. Relying solely on expenditure shares therefore leads to an underestimation of sectoral productivity growth for large exporters (e.g., non-agriculture in China and India). This pattern is evident in Figure C.10, which shows that the model provides a poorer fit to the observed APG dynamics than the baseline open-economy model, especially for countries such as China and India. Moreover, we observe that the model tends to under-predict the increase in APG for certain countries, such as Turkey. This is because their agricultural consumption share has declined little or only gradually. In the closed-economy model, the value-added share corresponds directly to the consumption share. Since we target the consumption share and employment gradually shifts out of agriculture, APG tends to decrease in these countries.

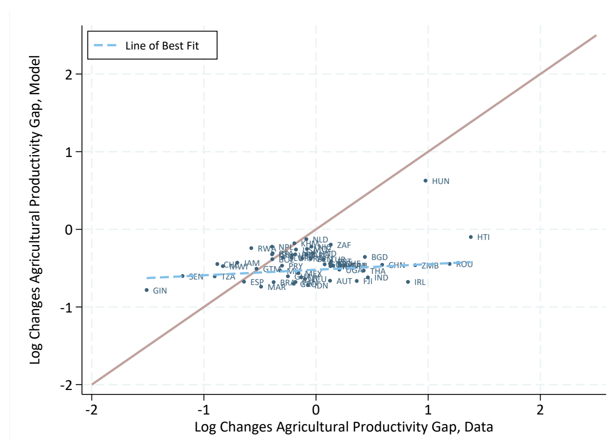
Figure C.10: Dynamics of APGs in Counterfactual Scenarios, Alternative Calibration



(a) Baseline Model



(b) Contribution of Productivity Growth



(c) Contribution of Sectoral Labor Movements