Online Appendix

"The Macroeconomics of Intensive Agriculture" by Timo Boppart, Patrick Kiernan, Per Krusell and Hannes Malmberg.

A Appendix to Section 2

This section provides details on the measurement exercise in Section 2. Below is details on all the basic data series apart from the land compensation shares, which is more complex and is explained in Section A.1.

Y: nominal aggregate output net of natural resources. Nominal GDP is defined as GDP at purchaser prices in current dollars and was obtained from the World Development Indicators (WDI). The share of natural resource rents in GDP, defined as natural resource income net of production costs, was also obtained from the WDI. To calculate $\mathbf{Y}$, we multiplied nominal GDP by (1 - share of natural resource rents).

$\mathbf{Y}_a/\mathbf{Y}$: Nominal agricultural output as a share of GDP. Nominal GDP is constructed as above. The main data source for agricultural output is UNSD System of National Accounts Statistics: Main Aggregates and Detailed Tables 2.3. We define agriculture as Section A, Division 01. National accounts data is in standard local currency, which we convert to current dollars using exchange rates from the WDI, or, when this is missing, from the Penn World Table 10. For countries that lack UN national accounts data on agricultural gross output, we use data from FAO.

H: Human capital per worker. We obtain Mincerian returns in 2005 from Caselli et al. (2014). For schooling, we use average schooling for individuals aged 15 to 64 in 2005 from Barro-Lee version 2.2 data. For Nigeria and and Ethiopia, we lack Barro-Lee data and use data from IPUMS. We calculate human capital as $H = e^{\text{Mincerian}\times\text{Average schooling}}$.

s_h: Labor compensation share. We take the labor compensation share from the Penn World Table. The Penn World Table constructs from wage data for employees. For self-employed people, they assign "mixed income" to labor if mixed income data is available. Alternatively, they assume that self-employed workers earn the average value added per worker in agriculture or the same wage as other employees, whichever leads to a lower labor share.

emp_a**: Employment share in agriculture.** We use microdata from IPUMS covering employed individuals in the age groups 15 to 64. Within this sample, we calculate the share of agricultural employment using the reported industry of employment (the INDGEN variable in IPUMS).

$\mathbf{P}_a$**: Agricultural output price index.** We back out the agricultural output index from FAO data as the ratio of nominal and real gross agricultural output in FAO.

$\mathbf{P}_k$ **and** $\mathbf{P}_c$**.** We back out the capital and consumer prices from the investment price index and the consumption price index in the Penn-World table, with the consumer price index being a weighted average of the household consumption and government consumption price indices, weighted by the respective expenditure shares.

$\mathbf{P}_x$**: Price index for outside-of-sector agricultural intermediate inputs.** For agricultural intermediate input prices, there are unfortunately no recent aggregate data available, with the last major FAO data set being from 1985. Lacking macro data, we proxy prices using bilateral trade data from BACI: we obtain prices of a selected sample of internationally traded fertilizers and pesticides and aggregate them based on their respective weights.

$\mathbf{K}/\mathbf{Y}, \mathbf{K}_a/\mathbf{Y}_a$**. Nominal capital-output ratio in the full economy and in agriculture.** Aggregate and agricultural output are constructed as above. The raw data underlying the agricultural capital stock is the current price net capital stock in agriculture, forestry and fishing obtained from the FAO, which we allocate between "Agriculture" and "Forestry and Fishing" in line with their nominal gross outputs. The total capital stock is the real Penn World Table capital stock multiplied by the price of investment goods.

L**. Quality-adjusted land.** We obtain data on total cropland in hectares from the FAO. For land quality, we use the estimates in Adamopoulos and Restuccia (2022) and normalize the US land quality to 1.

I/Y: Nominal investment to output ratio. We use the share of investment expenditure in GDP from the PWT deflated by one minus the share of natural resource rents.

$s_{a,x}$ **intermediate input costs as shares of total agricultural revenue.** Intermediate input shares are calculated using data on intermediate input use in agriculture from the UN. The share is defined relative to gross output net of within-sector inputs. To adjust for within-sector intermediates, we use data from the

WIOD when it is available, and otherwise use a predicted within-sector intermediate input share based on WIOD and log GDP per worker.

A.1 Land share measurement

Measurement For EU and the US, we calculate the rental share of gross output by calculating total rental payments from the amount of arable land from the FAO and average rental rates from EUROSTAT and USDA, which we divide by agricultural gross outputs. For poor countries, we use a microdata based approach where we construct land shares from the farmer surveys LSMS for Sub-Saharan African countries and VDSA for India and Bangladesh. In these surveys, we focus on the subset of plots that are rented. For this subset, we sum using household weights to calculate total rental payments and total gross output, and we define the land share as the ratio of rental payments to total gross output. Figure A2 shows the results of the microdata exercise. We see that the land shares vary from a bit over 10% in Nigeria to 35% in Bangladesh, with most values being between 17% and 27%.

Comparison to existing estimates For the poorest countries in our sample, we find a land compensation share that is on average just above 20%. This number contrasts to a stylized fact in the development literature, which is that sharecropping contracts typically stipulate a 50/50 sharing of output between tenant and landlord (Mundlak, 2005).

A closer study of the Malawi LSMS data suggests that plausible explanation for ou the difference is heterogeneous land compensation shares by farm size. Among small farmers, rental shares are higher, which means that the typical farmer faces a high rental rate as a share of their output, consistent with the stylized fact from the sharecropping literature. However, given our macroeconomic focus, we focus on total rent payments over total output, which means that we implicitly weight farms by output, which means that we place high weights on large farms with low land shares.

For illustration, figure A3 shows the relationship between household output and the rental shares. We see that there is a strong negative correlation where small producers face high rental shares and large producers face lower rental shares. The implication is that the average rental rate weighted by households is more than twice as big as when we weight by output (26% vs 12%). When we consider the Bangladeshi data, we see similar patterns. Thus, we believe one plausible reconciliation between our finding and the higher values cited as stylized facts is that the land share is considerably higher for the typical farmer compared to the typical unit of output.[36]

[36]Our Malawi estimate at 13% is also lower than the 37% found in the same data in Chen et al. (2022a). After discussions

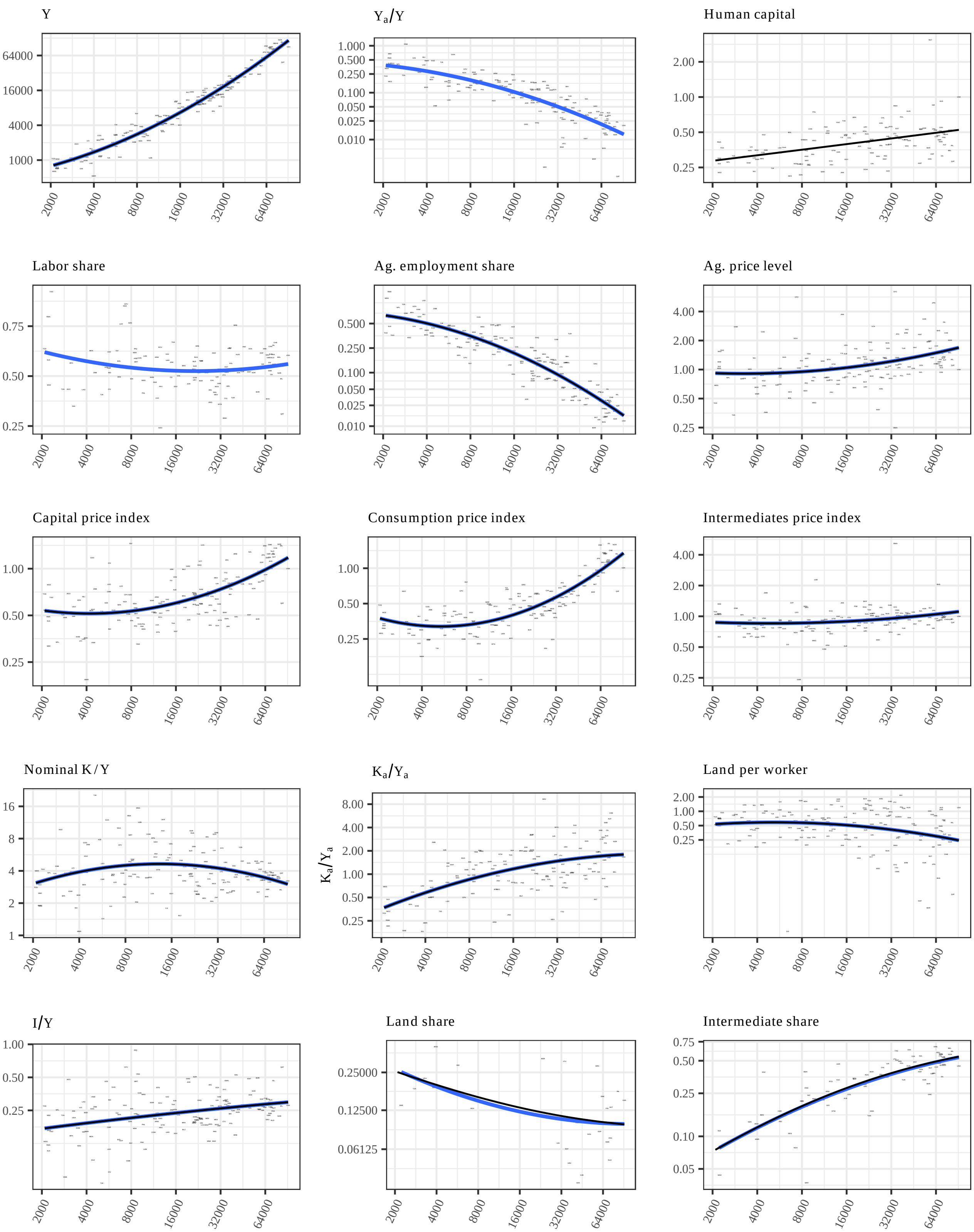

Figure A1: Basic data series together with projection

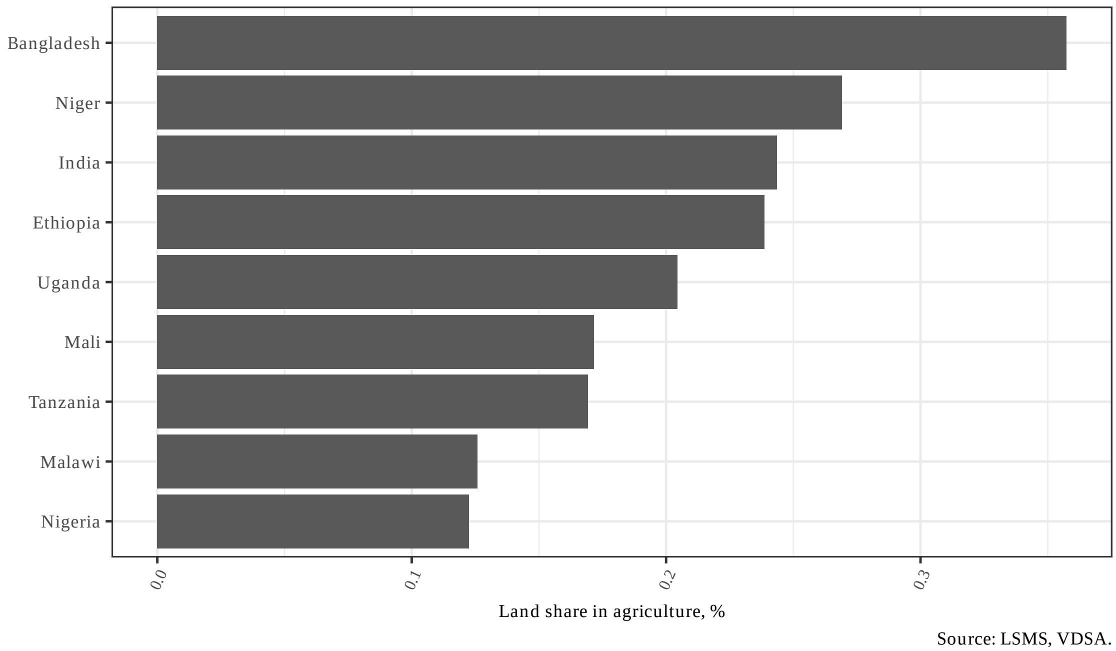

Figure A2: Micro-based land shares

B Appendix to Section 3

As stated in the main text, agricultural TFP is defined using the following equation:

$$d\log \mathbf{A}_a = d\log \mathbf{y}_a - \mathbf{s}_{a,h} d\log \mathbf{h}_a - s_{a,k} d\log \mathbf{k}_a - \mathbf{s}_{a,x} d\log \mathbf{x}_a - \mathbf{s}_{a,l} d\log \mathbf{L}.$$

To derive non-agricultural TFP differences, we need to address the fact that the allocation of factors across non-agricultural subsectors is not observed. However, given that their isoquants are the same, so are their factor ratios,

$$\frac{\mathbf{h}_{n,c}}{\mathbf{k}_{n,c}} = \frac{\mathbf{h}_{n,i}}{\mathbf{k}_{n,i}} = \frac{\mathbf{h}_{n,x}}{\mathbf{k}_{n,x}}$$

with the authors, our best conjecture is that the difference reflects them reporting a land share as a share of value added rather than gross output. One conjecture for the high implied intermediate input share in their paper is that Malawi ran an aggresive fertilizer subsidy program at the time of the survey, which can result in a high intermediate input shares if one uses market prices to calculate the nominal value of intermediate inputs.

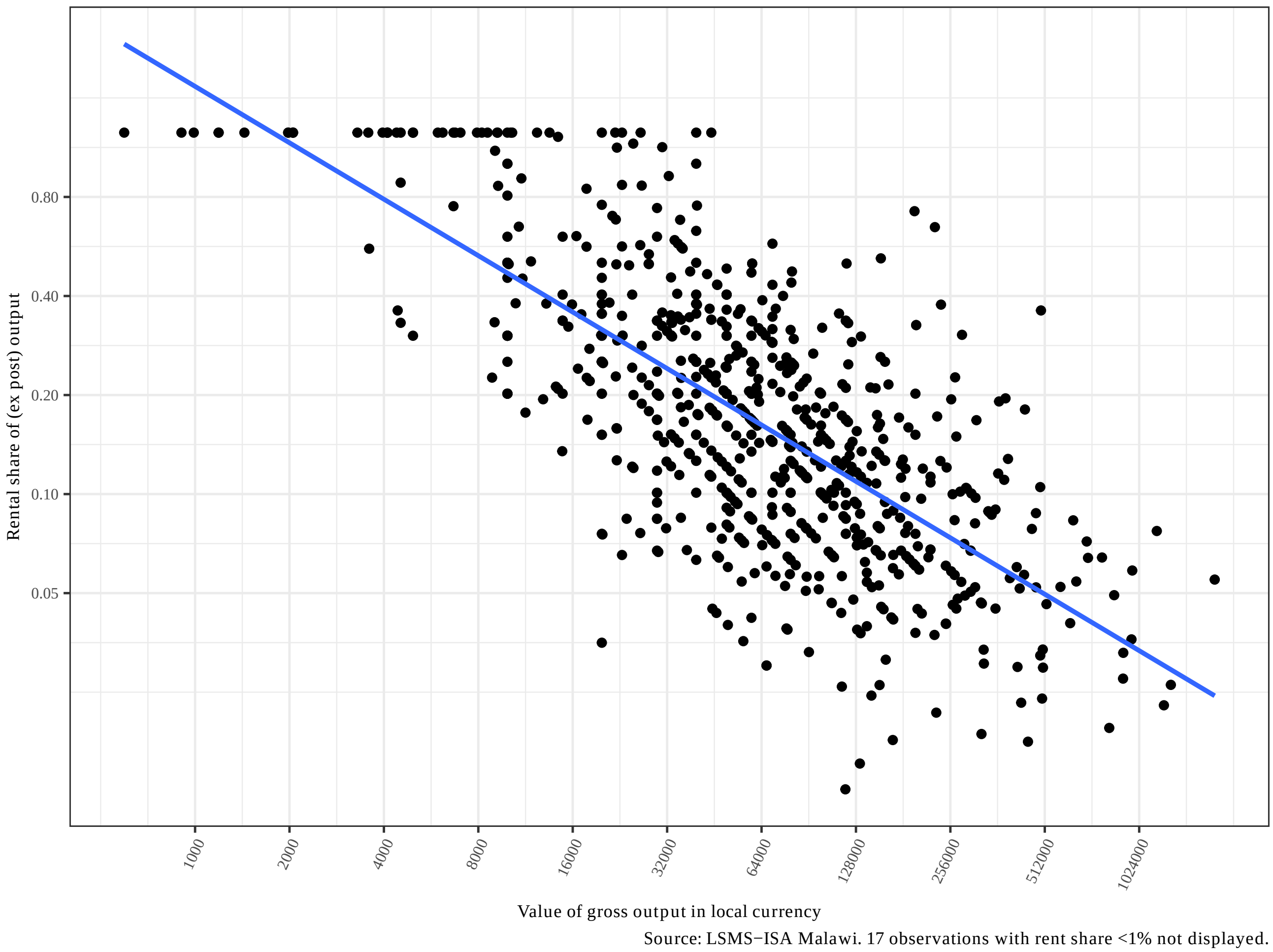

Figure A3: Output and land share by household in Malawi

Each observation represents a household in the 2016-2017 LSMS survey in Malawi. The share data is Winsorized at the top. 17 values out of 772 with rental shares below 1% are not displayed in the plot.

Thus, we obtain

$$\begin{aligned}
\mathbf{p}_n\mathbf{c}_n + \mathbf{p}_I \boldsymbol{i} + \mathbf{p}_x\mathbf{x}_a &= \mathbf{p}_n A_n g\left(\mathbf{h}_{n,c}, \mathbf{k}_{nc}\right) + \mathbf{p}_I \mathbf{A}_n \mathbf{A}_I g\left(\mathbf{h}_{n,I}, \mathbf{k}_{n,I}\right) + \mathbf{p}_x \mathbf{A}_n \mathbf{A}_x g(\mathbf{h}_{n,X}, \mathbf{k}_{n,X}) \\
&= \mathbf{p}_n \mathbf{A_n} \left[\mathbf{h}_{n,c} + \mathbf{h}_{n,I}\frac{\mathbf{p}_I}{\mathbf{p}_n}\mathbf{A}_I + \mathbf{h}_{n,x}\frac{\mathbf{p}_x}{\mathbf{p}_n}\mathbf{A}_x\right] g\left(1, \frac{\sum_{j\in\{c,I,x\}}\mathbf{k}_{n,j}}{\sum_{j\in\{c,I,x\}}\mathbf{h}_{n,j}}\right) \\
&= \mathbf{p}_n \mathbf{A}_n g\left(\mathbf{h}_n, \mathbf{k}_n\right),
\end{aligned}$$

where the last line uses $\mathbf{k}_n = \sum_{j\in\{c,I,x\}}\mathbf{k}_{n,j}$, $\mathbf{h}_n = \sum_{j\in\{c,I,x\}}\mathbf{h}_{n,j}$, $\mathbf{A}_I = \frac{\mathbf{p}_I}{\mathbf{p}_N}$, and $\mathbf{A}_x = \frac{\mathbf{p}_x}{\mathbf{p}_N}$. Define non-agricultural real output

$$\mathbf{y}_n = \frac{\mathbf{Y}_n}{\mathbf{p}_n}$$

Then, differences in non-agricultural TFP satisfy

$$d\log\mathbf{A}_n = d\log\mathbf{y}_n - \mathbf{s}_{h,n} d\log\mathbf{h}_n - \mathbf{s}_{k,n} d\log\mathbf{k}_n,$$

and the TFP-differences in the subsectors satisfy

$$\begin{aligned}
d\log\mathbf{A}_I = -d\log\frac{\mathbf{p}_I}{\mathbf{p}_n} \quad &\Longrightarrow \quad d\log\mathbf{A}_n\mathbf{A}_I = d\log\mathbf{A}_n - d\log\frac{\mathbf{p}_I}{\mathbf{p}_N} \\
d\log\mathbf{A}_x = -d\log\frac{\mathbf{p}_x}{\mathbf{p}_n} \quad &\Longrightarrow \quad d\log\mathbf{A}_n\mathbf{A}_I = d\log\mathbf{A}_n - d\log\frac{\mathbf{p}_x}{\mathbf{p}_N}.
\end{aligned}$$

Using these expressions, TFPs relative to the U.S. are given by

$$\log\left(\frac{A_z(y)}{A_z(y_{US})}\right) = \int_{y_{US}}^{y} d\log A_z(y) \quad z \in \{a, n, k, x\}$$

Estimating the CES parameters

- All our production functions can be decomposed as a chain of CES with two inputs
- For any two-input CES

  $$\mathbf{Q} = \left(\mathbf{Nest}_1^{\frac{\sigma-1}{\sigma}} + \omega \times \mathbf{Nest}_2^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}$$

  with quantity functions $\mathbf{Nest}_1$ and $\mathbf{Nest}_2$ and price functions $\mathbf{p}_{Nest_1}$ and $\mathbf{p}_{Nest_2}$, the first order condition is

  $$\log\frac{\mathbf{p}_{Nest_2}}{\mathbf{p}_{Nest_1}} = \log\omega - \frac{1}{\sigma}\log\left(\frac{\mathbf{Nest}_2}{\mathbf{Nest}_1}\right)$$

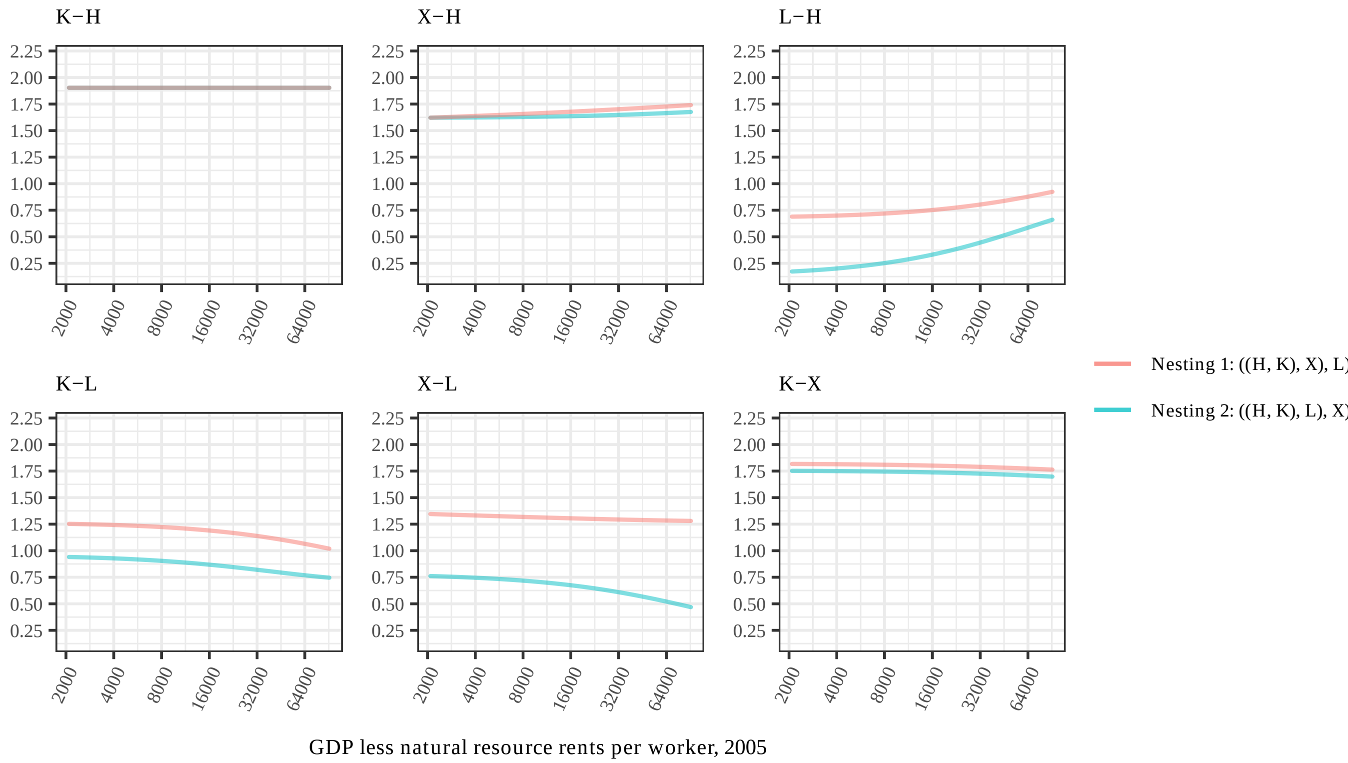

Figure A4: Morishima elasticities for alternative nest

- To estimate ω and σ, we pick the values that perfectly fit the price and quantity data from the poorest and richest countries, where we define the poorest countries as a country with a real GDP per worker of $\$2,000$ and the richest country as a country which is as rich as the United States.
- Given estimates of $\hat{\sigma}, \hat{\omega}$, we obtain an estimate $\hat{\mathbf{Q}}$ for the $\mathbf{Q}$-function.
- Having a procedure to estimate $\hat{\mathbf{Q}}$, we can recursively estimate all varieties in the nested CES by opening up each nest until it only consists of primitive relative factor functions and relative price functions, which were both estimated in section 2.

Alternative nestings

We considered on additional nestings in addition to the structure in equation (8). Focusing on nestings that combined capital and labor, this gave us two other nestings: one that switches the order between x and l above, and one which has two separate nests for $h - k$ and one for $x - l$. Figure A4 shows the Morishima elasticities for the two different nestings. we see that the elasticities are similar in general, apart from nestings that involve land, where the second nesting has somewhat lower elasticity.

Estimating preferences

PIGL estimation

- For a given set of parameters, the PIGL predicts a function of expenditure shares

$$\mathbf{s}_{a,c}^{pigl}(\cdot;\nu,\vartheta,\eta) = \nu \left(\frac{\mathbf{C}}{\mathbf{p}_n}\right)^{\vartheta-1} \mathbf{p}_a^{1-\eta}$$

- The parameters are estimated by the minimization problem

$$\hat{\nu}, \hat{\vartheta}, \hat{\eta} = \arg \min_{(\nu,\vartheta,\eta)\geq 0} \int_{\underline{y}}^{\bar{y}} \left[\log \mathbf{s}_{a,c}^{pigl}(y;\nu,\vartheta,\eta) - \log \mathbf{s}_{a,c}(y)\right]^2 dy$$

  subject to

$$\mathbf{s}_{a,c}^{pigl}(y_{US};\nu,\vartheta,\eta) = \mathbf{s}_{a,c}(y_{US})$$

- The constraint implies a function $\nu(\vartheta,\eta)$ for the share parameter ν and we can define the estimation as

$$\hat{\vartheta}, \hat{\eta} = \arg \min_{(\vartheta,\eta)\geq 0} \int_{\underline{y}}^{\bar{y}} \left[\log \mathbf{s}_{a,c}^{pigl}(y;\nu[\vartheta,\eta],\vartheta,\eta) - \log \mathbf{s}_{a,c}(y)\right]^2 dy$$

  with $\hat{v} = v(\hat{\vartheta},\hat{\eta})$.

- The minimization problem yields a one-dimensional space $(\hat{\vartheta},\hat{\eta})$ of minimizers. We select the minimizer with $\hat{\eta} = 0$ where the non-negativity constraint on η is binding, yielding a predicted function of agricultural expenditure shares:

$$\hat{\mathbf{s}}^{pigl} = \hat{\nu} \left(\frac{\mathbf{C}}{\mathbf{p}_n}\right)^{\hat{\vartheta}-1} \mathbf{p}_a$$

Stone-Geary estimation

- Given Stone-Geary preferences, the share is given by

$$\mathbf{s}_{a,c}^{SG}(\cdot;\bar{c}_a,\theta) = \frac{1}{E}\left[\mathbf{p}_a\bar{c}_a + \theta(\mathbf{E} - \mathbf{p}_a\bar{c}_a)\right]$$

- The estimators are defined as a minimizer

$$\hat{\bar{c}}_a = \arg \min_{\bar{c}_a} \int_{\underline{y}}^{\bar{y}} \left[\log \mathbf{s}_{a,c}^{SG}(y;\bar{c}_a,\theta(\bar{c}_a)) - \log \mathbf{s}_{a,c}(y)\right]^2 dy$$

where $\theta(\bar{c}_a) = \min_\theta [\mathbf{s}^{SG}_{a,c}(y_{US}; \bar{c}_a, \theta) - \mathbf{s}_{a,c}(y_{US})]^2$ is the share parameter that is closest to the consumption share at the U.S. income level.

C Appendix to Section 7

C.1 Model calibration

- The model has
  - 12 global parameters
    * 1: Time preference β
    * 2–3: Non-agricultural production function shape parameters ω^n_k, σ^n
    * 4–9: Agricultural production function shape parameters $\omega_1, \omega_2, \omega_3, \sigma_1, \sigma_2, \sigma_3$
    * 10–12: Consumption preference parametersν, ϑ, η
  - 10 country-varying parameters
    * 1–4: A_a, A_n, A_k, A_x (TFPs)
    * 5–7: H, gap, τ_h (human capital per worker and human capital + wage advantage of non-agricultural workers)
    * 8–9: δ, τ_k (depreciation rate and capital wedge)
    * 10: L (land per worker)
- For the global parameters, the production parameters are estimated in section 4 and the consumption preference parameters in section 3, leaving only the time preference parameter β.
- For the local parameters, the human capital level H, gap function gap, and the land per worker level L are defined in Section 2, where we also assumed $\tau_h = \mathbf{0}$
- The TFP functions solve the differential equations

$$
\begin{aligned}
d\log A_a &= d\log \mathbf{y}_a - \mathbf{s}_{h,a} d\log \mathbf{h}_a - s_{k,a} d\log \mathbf{k}_a - \mathbf{s}_{x,a} d\log \mathbf{x}_a - \mathbf{s}_{L,a} d\log \mathbf{L} \\
d\log A_n &= d\log \mathbf{y}_n - \mathbf{s}_{h,n} d\log \mathbf{h}_n - \mathbf{s}_{k,n} d\log \mathbf{k}_n \\
d\log A_I &= -d\log \frac{\mathbf{p}_I}{\mathbf{p}_n} \\
d\log A_x &= -d\log \frac{\mathbf{p}_x}{\mathbf{p}_n}
\end{aligned}
$$

subject to the initial conditions

$$
\begin{aligned}
A_a(y_{US}) &= \frac{\hat{q}_a[\mathbf{w}(y_{US}), \mathbf{r}(y_{US}), \mathbf{p}_x(y_{US}), \mathbf{p}_L(y_{US})]}{\mathbf{p}_a(y_{US})} \\
A_n(y_{US}) &= \frac{\hat{q}_n[\mathbf{w}(y_{US}), \mathbf{r}(y_{US})]}{\mathbf{p}_n(y_{US})} \\
A_I(y_{US}) &= \frac{\mathbf{p}_n(y_{US})}{\mathbf{p}_I(y_{US})} \\
A_X(y_{US}) &= \frac{\mathbf{p}_n(y_{US})}{\mathbf{p}_X(y_{US})}
\end{aligned}
$$

- The differential equations coincide with those used to estimate TFP differences in Section 2. The initial condition targets the price level at the U.S. income level using the cost functions $\hat{q}_a$ and $\hat{q}_n$ which are constant across countries and obtained from the production function shape estimation in Section 3.
- This leaves us with δ, τ_k for the local parameters. Together with the time preference parameter, these are obtained by

$$
\begin{aligned}
\delta &= \frac{\mathbf{I}/\mathbf{Y}}{\mathbf{K}/\mathbf{Y}} \\
\beta &= (\mathbf{R}(y_{us}) + 1 - \delta)^{-1} \\
1 - \tau_k &= \frac{1/\beta - 1 + \delta}{\mathbf{R}} = \frac{\mathbf{R}(y_{us})}{\mathbf{R}}
\end{aligned}
$$

where we note that δ and τ_k are functions and β is a scalar.

C.2 Model solution and counterfactuals

- The model solution is obtained by feeding the function for local parameters and the global parameters. It returns a set of (differentiable) functions which give the endogenous outcomes associated with different income levels.
- In all exercises, we define real GDP per worker via the differential equation and initial value

$$
d\log \mathbf{y}_{real} = \mathbf{s}_I d\log \mathbf{I}/_{\mathbf{k}} + \mathbf{s}_c \mathbf{s}_{a,c} d\log \mathbf{c_a} + \mathbf{s}_c \mathbf{s}_{n,c} d\log \mathbf{c}_n \qquad \log \mathbf{y}_{real}(y_{us}) = \log y_{us}
$$

where the differential term use that changes in GDP are given by changes in final expenditures weighted by their share in final expenditure and the initial value ensures that the levels match at the U.S. income level.

- When only changing agricultural TFP, we do the same exercise but replacing the functions A_n, A_k, A_x with

$$A_n^{\text{only ag}}(y) \equiv A_n(y_{poor}), \quad A_k^{\text{only ag}}(y) \equiv A_k(y_{poor}), \quad A_x^{\text{only ag}}(y) \equiv A_x(y_{poor})$$

- When only changing non-agricultural, we do the same exercise but replacing A_a with

$$A_a^{\text{only non-ag}}(y) \equiv A_a(y_{poor})$$

- Under the land counterfactual, we lock all parameters at their value for y_{poor}, and consider the effect of changing land L from $L(y_{poor})$ to $0.2L(y_{poor})$.

C.3 Comparing our real income with the Penn World Table

Our chain-weighting approach to real income measure is similar to the one used by national statistics offices when calculating real GDP changes over time. However, it is different from the method used by the Penn World Table and the International Comparison Project, which cannot impose our assumptions of one-dimensional variation in all variables. Figure A5 compares our measure to the Penn World Table by calculating our chain-weighted measure for each income level y using the integral

$$y^{our}(y) = y^{US} + \int_{y^{US}}^{y} \left[s_a(y)\frac{d\log c_a(y)}{dy} + s_n(y)\frac{d\log c_n(y)}{dy} + s_i(y)\frac{d\log[\delta(y)k(y)]}{dy} \right] dy,$$

where all the functions are our data measures. If our measure agrees with the Penn World Table measure, this estimated output should be on the 45-degree line, given that we use Penn World Table real output per worker as our development index y. As seen in the figure, they are not precisely on the line, but they are very close. This shows that for the purpose of comparing rich and poor countries, you get a similar result to the Penn World Table aggregation procedure by simply projecting prices and expenditure shares on the log GDP dimension and doing chain-based real GDP calculations as is done over time within countries.

C.4 Tables

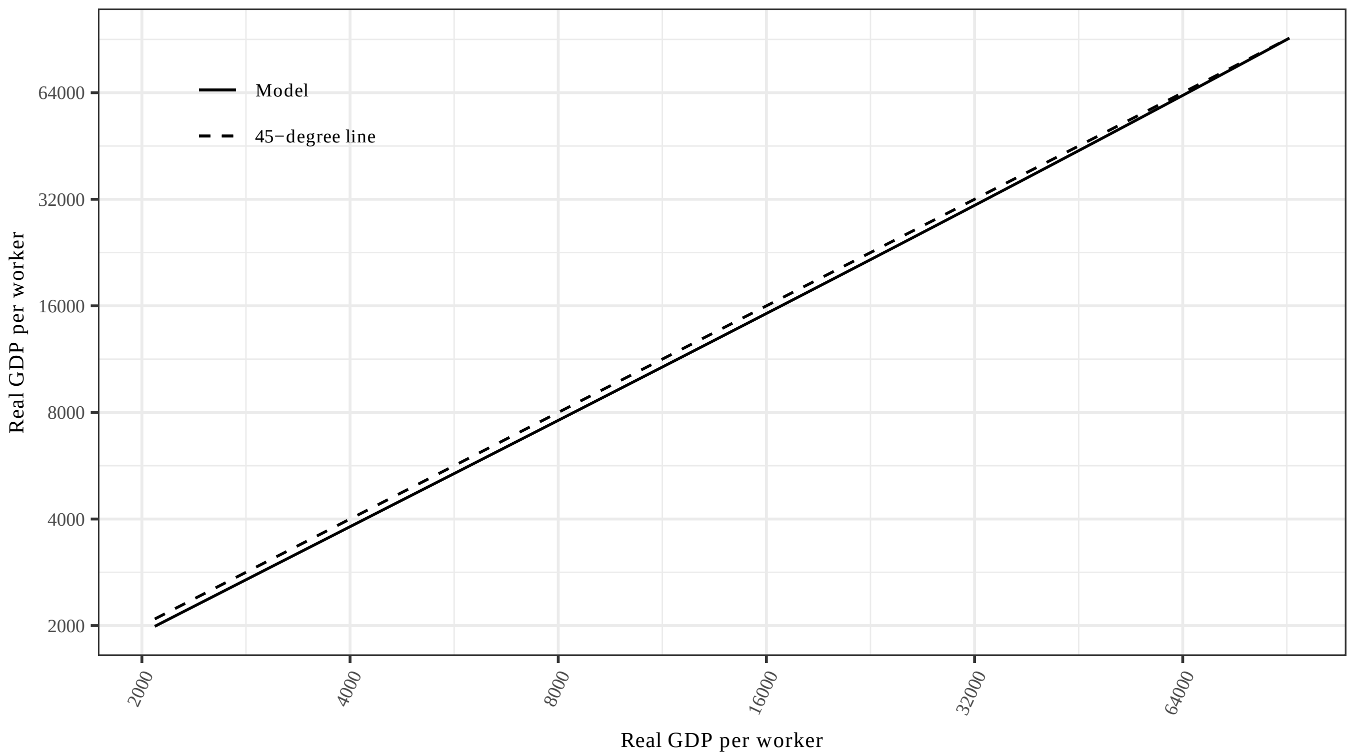

Figure A5: Comparison of a chain-weighted GDP measure with the Penn World Table

Table A1: Non-linearities in A_a, A_n, starting from poor

	Levels	A_a: Elasticity	A_a: +1 log	A_n: Elasticity	A_n: +1 log
$\log(r/w_a)$	-10.51	0.00	0.00	0.00	0.00
$\log(p_x/w_a)$	-7.61	0.00	0.00	0.00	0.00
$\log(p_l/w_a)$	-2.71	-1.91	-1.81	0.58	0.60
$\log(k_a/h_a)$	7.48	0.00	0.00	-0.00	-0.00
$\log(x_a/h_a)$	5.35	-0.51	-0.38	0.15	0.17
$\log(L/h_a)$	1.62	1.26	1.19	-0.38	-0.39
$\log(y_a/h_a)$	8.18	1.25	1.19	-0.08	-0.08
s_h^{ag}	0.67	0.12	0.10	-0.04	-0.04
s_k^{ag}	0.03	0.01	0.00	-0.00	-0.00
s_x^{ag}	0.07	-0.02	-0.02	0.01	0.01
s_l^{ag}	0.23	-0.11	-0.09	0.03	0.03
$\log(h_a/H)$	-1.00	-1.26	-1.19	0.38	0.39
$\log(k_n/h_n)$	10.43	0.00	0.00	-0.00	-0.00
$\log(y_n/h_n)$	9.33	-0.00	-0.00	1.00	1.00
$\log(e)$	7.72	-0.07	-0.02	1.02	1.03
$\log(p_a)$	0.85	-1.43	-1.33	1.13	1.15
s_k	0.35	0.20	0.10	-0.06	-0.08
s_h	0.58	-0.06	-0.04	0.02	0.02
s_l	0.07	-0.15	-0.06	0.04	0.06
$domar_a$	0.32	-0.49	-0.24	0.15	0.20
$domar_n$	0.46	0.36	0.18	-0.11	-0.15
$domar_i$	0.22	0.13	0.06	-0.04	-0.05
$domar_x$	0.02	-0.04	-0.02	0.01	0.02
$\log(c_a)$	5.92	-0.01	-0.00	0.31	0.31
$\log(c_n)$	7.19	0.89	0.39	0.73	0.58
$\log(\delta k)$	5.86	0.68	0.32	-0.21	-0.30
$\log(y)$		0.55	0.29	0.39	0.30

Table A2: Non-linearities in A_nA_k and A_nA_x starting from poor

	Levels	A_nA_k: Elasticity	A_nA_k: + 1 log	A_nA_x: Elasticity	A_nA_x: + 1 log
$\log(r/w_a)$	-10.51	-1.92	-1.90	0.00	0.00
$\log(p_x/w_a)$	-7.61	-0.92	-0.90	-1.00	-1.00
$\log(p_l/w_a)$	-2.71	0.25	0.11	-0.24	-0.32
$\log(k_a/h_a)$	7.48	3.65	3.62	0.00	0.00
$\log(x_a/h_a)$	5.35	1.72	1.70	1.69	1.67
$\log(L/h_a)$	1.62	-0.06	0.19	0.16	0.21
$\log(y_a/h_a)$	8.18	0.23	0.48	0.15	0.21
s_h^{ag}	0.67	-0.11	-0.16	-0.02	-0.03
s_k^{ag}	0.03	0.05	0.11	-0.00	-0.00
s_x^{ag}	0.07	0.05	0.05	0.05	0.06
s_l^{ag}	0.23	0.01	0.01	-0.03	-0.03
$\log(h_a/H)$	-1.00	0.06	-0.19	-0.16	-0.21
$\log(k_n/h_n)$	10.43	1.88	1.86	0.00	0.00
$\log(y_n/h_n)$	9.33	0.90	0.88	-0.00	-0.00
$\log(e)$	7.72	0.94	0.94	-0.01	-0.01
$\log(p_a)$	0.85	0.85	0.70	-0.12	-0.17
s_k	0.35	-0.01	0.03	0.03	0.03
s_h	0.58	-0.01	-0.04	-0.01	-0.01
s_l	0.07	0.02	0.00	-0.02	-0.02
$domar_a$	0.32	0.06	0.01	-0.04	-0.05
$domar_n$	0.46	-0.06	-0.03	0.03	0.03
$domar_i$	0.22	-0.01	0.02	0.02	0.02
$domar_x$	0.02	0.02	0.02	0.01	0.01
$\log(c_a)$	5.92	0.28	0.29	-0.00	-0.00
$\log(c_n)$	7.19	0.81	0.91	0.07	0.09
$\log(\delta k)$	5.86	1.90	2.05	0.08	0.10
$\log(y)$		0.88	0.96	0.05	0.06

Table A3: Non-linearities in H, starting from poor

	Levels	H: Elasticity	H: + one log-point
$\log(r/w_a)$	-10.51	0.00	0.00
$\log(p_x/w_a)$	-7.61	0.00	0.00
$\log(p_l/w_a)$	-2.71	0.59	0.59
$\log(k_a/h_a)$	7.48	0.00	0.00
$\log(x_a/h_a)$	5.35	0.16	0.17
$\log(L/h_a)$	1.62	-0.39	-0.39
$\log(y_a/h_a)$	8.18	-0.08	-0.08
s_h^{ag}	0.67	-0.04	-0.04
s_k^{ag}	0.03	-0.00	-0.00
s_x^{ag}	0.07	0.01	0.01
s_l^{ag}	0.23	0.03	0.03
$\log(h_a/H)$	-1.00	-0.61	-0.61
$\log(k_n/h_n)$	10.43	0.00	0.00
$\log(y_n/h_n)$	9.33	0.00	-0.00
$\log(e)$	7.72	1.02	1.01
$\log(p_a)$	0.85	0.13	0.14
s_k	0.35	0.08	0.06
s_h	0.58	-0.05	-0.03
s_l	0.07	-0.04	-0.03
$domar_a$	0.32	-0.20	-0.15
$domar_n$	0.46	0.15	0.11
$domar_i$	0.22	0.05	0.04
$domar_x$	0.02	-0.01	-0.01
$\log(c_a)$	5.92	0.31	0.31
$\log(c_n)$	7.19	1.41	1.27
$\log(\delta k)$	5.86	1.33	1.22
$\log(y)$		1.04	1.02

Table A4: Non-linearities in A_a, A_n, starting from rich

	Levels	A_a: Elasticity	A_a: +1 log	A_n: Elasticity	A_n: +1 log
$\log(r/w_a)$	-13.52	0.00	0.00	0.00	0.00
$\log(p_x/w_a)$	-11.64	0.00	0.00	0.00	0.00
$\log(p_l/w_a)$	-5.34	-1.48	-1.49	0.45	0.45
$\log(k_a/h_a)$	13.21	0.00	0.00	-0.00	-0.00
$\log(x_a/h_a)$	12.08	-0.22	-0.18	0.07	0.07
$\log(L/h_a)$	4.05	0.98	0.99	-0.30	-0.30
$\log(y_a/h_a)$	12.49	0.98	0.99	0.01	0.01
s_h^{ag}	0.28	0.04	0.03	-0.01	-0.01
s_k^{ag}	0.21	0.03	0.02	-0.01	-0.01
s_x^{ag}	0.44	-0.04	-0.03	0.01	0.01
s_l^{ag}	0.08	-0.03	-0.03	0.01	0.01
$\log(h_a/H)$	-4.82	-0.98	-0.99	0.30	0.30
$\log(k_n/h_n)$	13.37	0.00	0.00	-0.00	-0.00
$\log(y_n/h_n)$	12.37	-0.00	-0.00	1.00	1.00
$\log(e)$	11.34	-0.00	-0.00	1.00	1.00
$\log(p_a)$	0.30	-1.11	-1.10	1.03	1.04
s_k	0.46	0.00	0.00	-0.00	-0.00
s_h	0.54	0.00	0.00	-0.00	-0.00
s_l	0.00	-0.00	-0.00	0.00	0.00
$domar_a$	0.02	-0.02	-0.01	0.01	0.01
$domar_n$	0.67	0.02	0.01	-0.01	-0.01
$domar_i$	0.32	0.00	0.00	-0.00	-0.00
$domar_x$	0.01	-0.01	-0.00	0.00	0.00
$\log(c_a)$	7.03	0.00	0.00	0.30	0.30
$\log(c_n)$	11.32	0.02	0.01	0.99	0.99
$\log(\delta k)$	10.41	0.00	0.00	-0.00	-0.00
$\log(y)$		0.02	0.01	0.67	0.66

Table A5: Non-linearities in A_nA_k and A_nA_x, starting from rich

	Levels	A_nA_k: Elasticity	A_nA_k: + 1 log	A_nA_x: Elasticity	A_nA_x: + 1 log
$\log(r/w_a)$	-13.52	-1.86	-1.85	0.00	0.00
$\log(p_x/w_a)$	-11.64	-0.86	-0.85	-1.00	-1.00
$\log(p_l/w_a)$	-5.34	-0.49	-0.44	-1.13	-1.31
$\log(k_a/h_a)$	13.21	3.55	3.51	0.00	0.00
$\log(x_a/h_a)$	12.08	1.68	1.78	1.58	1.59
$\log(L/h_a)$	4.05	1.30	1.72	0.75	0.87
$\log(y_a/h_a)$	12.49	1.56	1.97	0.75	0.87
s_h^{ag}	0.28	-0.21	-0.18	-0.06	-0.07
s_k^{ag}	0.21	0.19	0.19	-0.05	-0.05
s_x^{ag}	0.44	0.02	-0.04	0.16	0.16
s_l^{ag}	0.08	0.00	0.02	-0.05	-0.04
$\log(h_a/H)$	-4.82	-1.30	-1.72	-0.75	-0.87
$\log(k_n/h_n)$	13.37	1.82	1.81	0.00	0.00
$\log(y_n/h_n)$	12.37	0.85	0.83	-0.00	0.00
$\log(e)$	11.34	0.86	0.84	-0.00	-0.00
$\log(p_a)$	0.30	0.07	-0.11	-0.52	-0.59
s_k	0.46	-0.01	-0.01	0.00	0.00
s_h	0.54	0.01	0.01	0.00	0.00
s_l	0.00	-0.00	-0.00	-0.00	-0.00
$domar_a$	0.02	-0.01	-0.01	-0.01	-0.01
$domar_n$	0.67	0.01	0.01	0.01	0.01
$domar_i$	0.32	-0.00	-0.01	0.00	0.00
$domar_x$	0.01	-0.00	-0.00	-0.00	-0.00
$\log(c_a)$	7.03	0.26	0.26	0.00	0.00
$\log(c_n)$	11.32	0.87	0.85	0.01	0.01
$\log(\delta k)$	10.41	1.84	1.81	0.00	0.00
$\log(y)$		1.17	1.15	0.01	0.01

Table A6: Non-linearities in H, starting from rich

	Levels	H: Elasticity	H: + one log-point
$\log(r/w_a)$	-13.52	0.00	0.00
$\log(p_x/w_a)$	-11.64	0.00	0.00
$\log(p_l/w_a)$	-5.34	0.45	0.45
$\log(k_a/h_a)$	13.21	0.00	0.00
$\log(x_a/h_a)$	12.08	0.07	0.07
$\log(L/h_a)$	4.05	-0.30	-0.30
$\log(y_a/h_a)$	12.49	0.01	0.01
s_h^{ag}	0.28	-0.01	-0.01
s_k^{ag}	0.21	-0.01	-0.01
s_x^{ag}	0.44	0.01	0.01
s_l^{ag}	0.08	0.01	0.01
$\log(h_a/H)$	-4.82	-0.70	-0.70
$\log(k_n/h_n)$	13.37	0.00	0.00
$\log(y_n/h_n)$	12.37	-0.00	-0.00
$\log(e)$	11.34	1.00	1.00
$\log(p_a)$	0.30	0.03	0.04
s_k	0.46	0.00	0.00
s_h	0.54	0.00	0.00
s_l	0.00	-0.00	-0.00
$domar_a$	0.02	-0.01	-0.01
$domar_n$	0.67	0.01	0.01
$domar_i$	0.32	0.00	0.00
$domar_x$	0.01	-0.00	-0.00
$\log(c_a)$	7.03	0.30	0.30
$\log(c_n)$	11.32	1.01	1.01
$\log(\delta k)$	10.41	1.00	1.00
$\log(y)$		1.00	1.00

Table A7: Complementarity test: +1log(A_a),log(A_n), starting from poor

	Levels	Δlog(A_a)= 1	Δlog(A_n)= 1	Additive	Non-linear
$\log(r/w_a)$	-10.51	0.00	0.00	0.00	0.00
$\log(p_x/w_a)$	-7.61	0.00	0.00	0.00	0.00
$\log(p_l/w_a)$	-2.71	-1.81	0.60	-1.21	-1.27
$\log(k_a/h_a)$	7.48	0.00	-0.00	-0.00	-0.00
$\log(x_a/h_a)$	5.35	-0.38	0.17	-0.21	-0.29
$\log(L/h_a)$	1.62	1.19	-0.39	0.80	0.84
$\log(y_a/h_a)$	8.18	1.19	-0.08	1.11	1.14
s_h^{ag}	0.67	0.10	-0.04	0.06	0.07
s_k^{ag}	0.03	0.01	-0.00	0.00	0.00
s_x^{ag}	0.07	-0.01	0.01	-0.01	-0.01
s_l^{ag}	0.23	-0.09	0.03	-0.05	-0.06
$\log(h_a/H)$	-1.00	-1.19	0.39	-0.80	-0.84
$\log(k_n/h_n)$	10.43	0.00	-0.00	-0.00	-0.00
$\log(y_n/h_n)$	9.33	-0.00	1.00	1.00	1.00
$\log(e)$	7.72	-0.02	1.03	1.02	0.98
$\log(p_a)$	0.85	-1.33	1.15	-0.18	-0.25
s_k	0.35	0.10	-0.08	0.02	0.08
s_h	0.58	-0.04	0.02	-0.02	-0.03
s_l	0.07	-0.06	0.06	0.00	-0.05
$domar_a$	0.32	-0.24	0.20	-0.04	-0.20
$domar_n$	0.46	0.18	-0.15	0.03	0.15
$domar_i$	0.22	0.06	-0.05	0.01	0.05
$domar_x$	0.02	-0.02	0.02	0.00	-0.02
$\log(c_a)$	5.92	-0.00	0.31	0.31	0.30
$\log(c_n)$	7.19	0.39	0.58	0.97	1.33
$\log(\delta k)$	5.86	0.32	-0.30	0.02	0.27
$\log(y)$		0.29	0.30	0.60	0.85

Table A8: Change $\log(A_a)$ from from poor to rich level ($\Delta\log(A_a)$= 1.84)

	Linear - poor	Linear - mid	Linear - rich	Non-linear	TFPs and H	All
$\log(r/w_a)$	0.00	0.00	0.00	0.00	-3.91	-3.01
$\log(p_x/w_a)$	0.00	0.00	0.00	0.00	-4.45	-4.03
$\log(p_l/w_a)$	-3.51	-3.22	-3.03	-3.21	-4.00	-2.63
$\log(k_a/h_a)$	0.00	0.00	0.00	0.00	7.43	5.73
$\log(x_a/h_a)$	-0.93	-0.57	-0.32	-0.57	7.40	6.73
$\log(L/h_a)$	2.32	2.12	2.00	2.12	3.92	2.43
$\log(y_a/h_a)$	2.29	2.13	2.01	2.12	5.16	4.32
s_h^{ag}	0.22	0.15	0.09	0.15	-0.47	-0.39
s_k^{ag}	0.01	0.01	0.00	0.01	0.30	0.17
s_x^{ag}	-0.04	-0.02	-0.01	-0.02	0.34	0.37
s_l^{ag}	-0.19	-0.14	-0.09	-0.13	-0.16	-0.15
$\log(h_a/H)$	-2.32	-2.12	-2.00	-2.12	-4.53	-3.82
$\log(k_n/h_n)$	0.00	0.00	0.00	0.00	3.82	2.95
$\log(y_n/h_n)$	-0.00	0.00	0.00	0.00	3.44	3.04
$\log(e)$	-0.12	0.00	0.01	-0.01	4.07	3.62
$\log(p_a)$	-2.63	-2.33	-2.12	-2.32	-0.47	-0.55
s_k	0.37	0.10	0.03	0.12	0.11	0.12
s_h	-0.10	-0.05	-0.02	-0.05	-0.04	-0.04
s_l	-0.27	-0.05	-0.01	-0.07	-0.07	-0.07
$domar_a$	-0.90	-0.25	-0.06	-0.29	-0.31	-0.30
$domar_n$	0.67	0.18	0.05	0.21	0.24	0.21
$domar_i$	0.23	0.06	0.02	0.08	0.07	0.10
$domar_x$	-0.08	-0.02	-0.00	-0.02	-0.02	-0.02
$\log(c_a)$	-0.02	0.01	0.00	0.00	1.24	1.11
$\log(c_n)$	1.63	0.38	0.10	0.47	4.58	4.13
$\log(\delta k)$	1.24	0.32	0.09	0.39	4.87	4.55
$\log(y)$	1.02	0.33	0.09	0.37	4.21	3.81

Table A9: Change $\log(A_n)$ from from poor to rich level ($\Delta\log(A_n)$= 1.65)

	Linear - poor	Linear - mid	Linear - rich	Non-linear	TFPs and H	All
$\log(r/w_a)$	0.00	0.00	0.00	0.00	-3.91	-3.01
$\log(p_x/w_a)$	0.00	0.00	0.00	0.00	-4.45	-4.03
$\log(p_l/w_a)$	0.96	1.01	1.07	1.01	-4.00	-2.63
$\log(k_a/h_a)$	-0.00	-0.00	-0.00	-0.00	7.43	5.73
$\log(x_a/h_a)$	0.25	0.31	0.36	0.30	7.40	6.73
$\log(L/h_a)$	-0.63	-0.66	-0.71	-0.66	3.92	2.43
$\log(y_a/h_a)$	-0.13	-0.15	-0.17	-0.15	5.16	4.32
s_h^{ag}	-0.06	-0.07	-0.08	-0.07	-0.47	-0.39
s_k^{ag}	-0.00	-0.00	-0.00	-0.00	0.30	0.17
s_x^{ag}	0.01	0.02	0.02	0.02	0.34	0.37
s_l^{ag}	0.05	0.06	0.07	0.06	-0.16	-0.15
$\log(h_a/H)$	0.63	0.66	0.71	0.66	-4.53	-3.82
$\log(k_n/h_n)$	-0.00	-0.00	-0.00	0.00	3.82	2.95
$\log(y_n/h_n)$	1.65	1.65	1.65	1.65	3.44	3.04
$\log(e)$	1.68	1.73	1.79	1.73	4.07	3.62
$\log(p_a)$	1.87	1.91	1.96	1.91	-0.47	-0.55
s_k	-0.10	-0.17	-0.26	-0.17	0.11	0.12
s_h	0.03	0.03	0.03	0.03	-0.04	-0.04
s_l	0.07	0.14	0.23	0.14	-0.07	-0.07
$domar_a$	0.25	0.42	0.65	0.41	-0.31	-0.30
$domar_n$	-0.18	-0.31	-0.48	-0.31	0.24	0.21
$domar_i$	-0.06	-0.11	-0.17	-0.11	0.07	0.10
$domar_x$	0.02	0.04	0.07	0.04	-0.02	-0.02
$\log(c_a)$	0.51	0.52	0.54	0.52	1.24	1.11
$\log(c_n)$	1.20	0.61	-1.51	0.51	4.58	4.13
$\log(\delta k)$	-0.34	-0.69	-1.50	-0.71	4.87	4.55
$\log(y)$	0.64	0.34	-0.01	0.37	4.21	3.81

Table A10: Change $\log(A_k)$ from from poor to rich level ($\Delta\log(A_k)$= 0.42)

	Linear - poor	Linear - mid	Linear - rich	Non-linear	TFPs and H	All
$\log(r/w_a)$	-0.81	-0.82	-0.81	-0.81	-3.91	-3.01
$\log(p_x/w_a)$	-0.39	-0.39	-0.38	-0.39	-4.45	-4.03
$\log(p_l/w_a)$	0.11	0.13	0.06	0.08	-4.00	-2.63
$\log(k_a/h_a)$	1.55	1.55	1.53	1.54	7.43	5.73
$\log(x_a/h_a)$	0.73	0.73	0.72	0.72	7.40	6.73
$\log(L/h_a)$	-0.02	-0.05	0.05	0.01	3.92	2.43
$\log(y_a/h_a)$	0.10	0.07	0.17	0.13	5.16	4.32
s_h^{ag}	-0.04	-0.04	-0.06	-0.05	-0.47	-0.39
s_k^{ag}	0.02	0.02	0.04	0.03	0.30	0.17
s_x^{ag}	0.02	0.02	0.02	0.02	0.34	0.37
s_l^{ag}	0.00	0.00	0.00	0.00	-0.16	-0.15
$\log(h_a/H)$	0.02	0.05	-0.05	-0.01	-4.53	-3.82
$\log(k_n/h_n)$	0.80	0.80	0.79	0.79	3.82	2.95
$\log(y_n/h_n)$	0.38	0.38	0.37	0.38	3.44	3.04
$\log(e)$	0.40	0.40	0.40	0.40	4.07	3.62
$\log(p_a)$	0.36	0.38	0.31	0.34	-0.47	-0.55
s_k	-0.00	-0.01	0.01	0.00	0.11	0.12
s_h	-0.00	0.00	-0.01	-0.01	-0.04	-0.04
s_l	0.01	0.01	0.00	0.01	-0.07	-0.07
$domar_a$	0.03	0.03	0.01	0.02	-0.31	-0.30
$domar_n$	-0.02	-0.03	-0.02	-0.02	0.24	0.21
$domar_i$	-0.00	-0.01	0.01	0.00	0.07	0.10
$domar_x$	0.01	0.01	0.01	0.01	-0.02	-0.02
$\log(c_a)$	0.12	0.12	0.12	0.12	1.24	1.11
$\log(c_n)$	0.34	0.33	0.37	0.35	4.58	4.13
$\log(\delta k)$	0.80	0.79	0.86	0.83	4.87	4.55
$\log(y)$	0.37	0.37	0.39	0.38	4.21	3.81

Table A11: Change $\log(A_x)$ from from poor to rich level ($\Delta\log(A_x)$= 0.96)

	Linear - poor	Linear - mid	Linear - rich	Non-linear	TFPs and H	All
$\log(r/w_a)$	0.00	0.00	0.00	0.00	-3.91	-3.01
$\log(p_x/w_a)$	-0.96	-0.96	-0.96	-0.96	-4.45	-4.03
$\log(p_l/w_a)$	-0.23	-0.21	-0.39	-0.30	-4.00	-2.63
$\log(k_a/h_a)$	0.00	0.00	0.00	0.00	7.43	5.73
$\log(x_a/h_a)$	1.63	1.63	1.59	1.61	7.40	6.73
$\log(L/h_a)$	0.15	0.14	0.26	0.20	3.92	2.43
$\log(y_a/h_a)$	0.15	0.14	0.26	0.20	5.16	4.32
s_h^{ag}	-0.02	-0.02	-0.04	-0.03	-0.47	-0.39
s_k^{ag}	-0.00	-0.00	-0.00	-0.00	0.30	0.17
s_x^{ag}	0.04	0.04	0.07	0.06	0.34	0.37
s_l^{ag}	-0.02	-0.02	-0.04	-0.03	-0.16	-0.15
$\log(h_a/H)$	-0.15	-0.14	-0.26	-0.20	-4.53	-3.82
$\log(k_n/h_n)$	0.00	0.00	0.00	0.00	3.82	2.95
$\log(y_n/h_n)$	-0.00	-0.00	-0.00	0.00	3.44	3.04
$\log(e)$	-0.01	-0.01	-0.01	-0.01	4.07	3.62
$\log(p_a)$	-0.12	-0.11	-0.20	-0.16	-0.47	-0.55
s_k	0.02	0.02	0.03	0.03	0.11	0.12
s_h	-0.01	-0.01	-0.01	-0.01	-0.04	-0.04
s_l	-0.02	-0.02	-0.02	-0.02	-0.07	-0.07
$domar_a$	-0.04	-0.04	-0.06	-0.05	-0.31	-0.30
$domar_n$	0.03	0.03	0.04	0.03	0.24	0.21
$domar_i$	0.02	0.01	0.02	0.02	0.07	0.10
$domar_x$	0.01	0.01	0.01	0.01	-0.02	-0.02
$\log(c_a)$	-0.00	-0.00	-0.00	-0.00	1.24	1.11
$\log(c_n)$	0.07	0.07	0.10	0.08	4.58	4.13
$\log(\delta k)$	0.08	0.08	0.10	0.09	4.87	4.55
$\log(y)$	0.05	0.05	0.07	0.06	4.21	3.81

Table A12: Change log(H) from from poor to rich level (Δlog(H)= 0.61)

	Linear - poor	Linear - mid	Linear - rich	Non-linear	TFPs and H	All
$\log(r/w_a)$	0.00	0.00	0.00	0.00	-3.91	-3.01
$\log(p_x/w_a)$	0.00	0.00	0.00	0.00	-4.45	-4.03
$\log(p_l/w_a)$	0.36	0.36	0.36	0.36	-4.00	-2.63
$\log(k_a/h_a)$	0.00	0.00	0.00	0.00	7.43	5.73
$\log(x_a/h_a)$	0.10	0.10	0.11	0.10	7.40	6.73
$\log(L/h_a)$	-0.24	-0.24	-0.24	-0.24	3.92	2.43
$\log(y_a/h_a)$	-0.05	-0.05	-0.05	-0.05	5.16	4.32
s_h^{ag}	-0.02	-0.02	-0.02	-0.02	-0.47	-0.39
s_k^{ag}	-0.00	-0.00	-0.00	-0.00	0.30	0.17
s_x^{ag}	0.00	0.00	0.01	0.00	0.34	0.37
s_l^{ag}	0.02	0.02	0.02	0.02	-0.16	-0.15
$\log(h_a/H)$	-0.37	-0.37	-0.37	-0.37	-4.53	-3.82
$\log(k_n/h_n)$	0.00	0.00	0.00	0.00	3.82	2.95
$\log(y_n/h_n)$	0.00	0.00	-0.00	-0.00	3.44	3.04
$\log(e)$	0.62	0.62	0.61	0.62	4.07	3.62
$\log(p_a)$	0.08	0.09	0.09	0.09	-0.47	-0.55
s_k	0.05	0.04	0.03	0.04	0.11	0.12
s_h	-0.03	-0.02	-0.02	-0.02	-0.04	-0.04
s_l	-0.02	-0.02	-0.02	-0.02	-0.07	-0.07
$domar_a$	-0.12	-0.10	-0.08	-0.10	-0.31	-0.30
$domar_n$	0.09	0.07	0.06	0.07	0.24	0.21
$domar_i$	0.03	0.03	0.02	0.03	0.07	0.10
$domar_x$	-0.01	-0.01	-0.00	-0.01	-0.02	-0.02
$\log(c_a)$	0.19	0.19	0.19	0.19	1.24	1.11
$\log(c_n)$	0.86	0.80	0.75	0.80	4.58	4.13
$\log(\delta k)$	0.81	0.76	0.73	0.76	4.87	4.55
$\log(y)$	0.63	0.63	0.62	0.63	4.21	3.81

Table A13: Change $\log(A_a)\log(A_a)\log(A_kAn)\log(A_xAn)\log(H)$ from poor to rich level ($\Delta\log(A_a)\log(A_a)\log(A_kAn)\log(A_xAn)\log(H)$)

	(1)	(2)	(3)	(4)	(5)
	$Linear-poor$	$Linear-mid$	$Linear-rich$	Non-linear	All pars
$\log(r/w_a)$	-3.72	-3.66	-3.56	-3.64	-3.36
$\log(p_x/w_a)$	-4.24	-4.18	-4.08	-4.16	-4.03
$\log(p_l/w_a)$	-4.55	-5.24	-6.33	-3.47	-2.04
$\log(k_n/h_n)$	3.62	3.56	3.47	3.55	3.27
$\log(k_a/h_a)$	5.76	5.66	5.51	5.63	5.20
$\log(x_a/h_a)$	6.01	5.89	5.76	6.04	5.96
$\log(L/h_a)$	4.86	5.74	7.32	4.02	2.49
$\log(y_a/h_a)$	5.71	6.50	8.03	4.77	4.48
$\log(e)$	2.62	2.33	2.20	2.32	3.63
$\log(p_a)$	-3.49	-4.09	-5.21	-2.22	-0.83
$\log(h_a/H)$	-5.46	-6.34	-7.92	-4.62	-3.91
s_k	0.82	0.13	-0.02	0.11	0.11
$domar_a$	-2.15	-0.48	-0.05	-0.36	-0.36
$domar_n$	1.68	0.41	0.06	0.30	0.25
$domar_i$	0.46	0.07	-0.01	0.06	0.11
$domar_x$	-0.24	-0.09	-0.02	-0.05	-0.05
$\log(c_a)$	0.85	0.76	0.72	0.76	1.18
$\log(c_n)$	7.16	3.06	2.28	2.93	4.23
$\log(\delta k)$	7.37	4.63	4.08	4.59	4.62
$\log(y)$	4.89	3.28	2.75	3.08	3.88

Table A14: Change τ_a, τ_k, L, δ from from poor to rich level

	Linear	Non-linear
$\log(r/w_a)$	0.82	0.93
$\log(p_x/w_a)$	0.39	0.45
$\log(p_l/w_a)$	-0.17	-0.20
$\log(k_a/h_a)$	-1.56	-1.77
$\log(x_a/h_a)$	-0.75	-0.85
$\log(L/h_a)$	0.07	0.09
$\log(y_a/h_a)$	-0.09	-0.07
s_h^{ag}	0.05	0.05
s_k^{ag}	-0.02	-0.02
s_x^{ag}	-0.02	-0.02
s_l^{ag}	-0.01	-0.01
$\log(h_a/H)$	-0.07	-0.09
$\log(k_n/h_n)$	-0.80	-0.91
$\log(y_n/h_n)$	-0.39	-0.44
$\log(e)$	-0.44	-0.48
$\log(p_a)$	-0.56	-0.62
s_k	0.01	0.02
s_h	0.00	-0.00
s_l	-0.01	-0.01
$domar_a$	-0.04	-0.05
$domar_n$	0.01	0.02
$domar_i$	0.04	0.03
$domar_x$	-0.01	-0.01
$\log(c_a)$	-0.16	-0.16
$\log(c_n)$	-0.38	-0.40
$\log(\delta k)$	-0.23	-0.32
$\log(y)$	-0.27	-0.31