

SUPPLEMENT TO “INVESTMENT DEMAND AND STRUCTURAL CHANGE”
(*Econometrica*, Vol. 89, No. 6, November 2021, 2751–2785)

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THIS SUPPLEMENT provides details on the data used in the paper (Appendix A), on our work with the WIOD (Appendix B), on the development regressions used to produce a stylized development process, (Appendix C), on the estimation details of the demand system (Appendix D.1), on the income elasticities implied by the estimated demand system (Appendix D.2), and on the estimation of some common restricted demand systems (Appendix D.3). In addition, there is a Web Appendix available from the authors’ web page with more details on the model (Appendix E) and on the shooting algorithm used to solve for the transitional dynamics (Appendix F).

APPENDIX A: DATA SOURCES AND SECTOR DEFINITIONS

We use four different data sources: the three described in this section and the WIOD described in Appendix B.

A.1. World Development Indicators (WDI)

We use the WDI database to obtain value added shares at current and at constant prices for our three sectors. The WDI divides the economy in three sectors: Agriculture (ISIC Rev 3.1 A and B), Industry (C to F), and Services (G to Q), which are the ones that we use.¹ In addition, we also use the variables for population and oil rents as a share of GDP in order to drop countries that are too small in terms of population and countries whose GDP is largely affected by oil extraction.

A.2. Groningen 10-Sector Database (G10S)

We use the G10S database to obtain value added shares at current and at constant prices for our three sectors. The G10S divides the economy in 10 industries, which we aggregate into our three main sectors mimicking the classification in WDI: Agriculture (ISIC Rev 3.1 A and B) contains “Agriculture”; Industry (C to F) contains “Mining,” “Manufacturing,” “Utilities,” “Construction”; and Services (G to Q) contains “Trade Services,” “Transport Services,” “Business Services,” “Government Services,” “Personal Services.”

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¹For some countries and years, it also provides a breakdown of the Industry category with the Manufacturing sector (D) separately.

A.3. Penn World Tables (PWT)

We use the 9.0 version of the PWT to obtain the series for the investment rate in LCU at current prices, the implicit price deflators for consumption and investment, the GDP per capita in constant LCU, and the GDP per capita in constant international dollars.

APPENDIX B: THE WORLD INPUT-OUTPUT TABLES

In this section, we provide more details on how we use the 2013 Release of the *World Input-Output Database* (WIOD) to construct some of the variables that we use in the paper. In particular, we explain (a) how we construct sectoral value added shares for consumption, investment, and exports for all countries and years, (b) how we aggregate from these sectoral value added shares by type of final good to sectoral value added shares of GDP, and (c) how we approximate the aggregation of sectoral value added shares without IO data.

B.1. Sectoral Value Added Shares in Consumption, Investment, and Exports

The 2013 Release of the WIOD provides national IO tables disaggregated into 35 industries for 40 countries and 17 years (the period 1995–2011). We aggregate the 35 different industries into agriculture, industry, and services using the same classification as in the other data sets (this means that agriculture is c1, industry is c2–c18, and services is c19–c35). Total production in each industry is either purchased by domestic industries (intermediate expenditure) or by final users (final expenditure), which include domestic final uses and exports. To measure how much domestic value added from each sector goes to each final use, we have to follow three steps. This procedure follows closely the material present in the Appendix of [Herrendorf, Rogerson, and Valentinyi \(2013\)](#).

First, we build three $(n \times 1)$ vectors, \mathbf{e}_C , \mathbf{e}_X , and \mathbf{e}_E , with the final expenditure in *consumption* (final consumption by households plus final consumption by non-profit organizations serving households plus final consumption by government), *investment* (gross fixed capital formation plus changes in inventories and valuables), and *exports* coming from each of the n sectors. Note that, in our case, the number of sectors is $n = 3$.

Second, we build the $(n \times n)$ Total Requirement (**TR**) matrix linking sectoral expenditure to sectoral production. In particular, the IO tables provided by the WIOD assume that each industry j produces only one commodity, and that each commodity i is used in only one industry.² Let \mathbf{A} denote the $(n \times n)$ transaction matrix, with entry ij showing the dollar amount of commodity i that industry j uses per dollar of output it produces. Let \mathbf{e} denote the $(n \times 1)$ final expenditure vector, where entry j contains the dollar amount of final expenditure coming from industry j . Note that $\mathbf{e} = \mathbf{e}_C + \mathbf{e}_X + \mathbf{e}_E$. Let \mathbf{g} denote the $(n \times 1)$ industry gross output vector, with entry j containing the total output in dollar amounts produced in industry j . Let \mathbf{q} denote the $(n \times 1)$ commodity gross output vector. The following identities link these three matrices with the (**TR**) matrix:

$$\mathbf{q} = \mathbf{A}\mathbf{g} + \mathbf{e},$$

$$\mathbf{q} = \mathbf{g}.$$

We first get rid of \mathbf{q} by using the second identity. We then solve for \mathbf{g} :

$$\mathbf{g} = (\mathbf{I} - \mathbf{A})^{-1}\mathbf{e},$$

²Notice that this structure is similar to the IO provided by the BEA prior to 1972.

where $\mathbf{TR} = (\mathbf{I} - \mathbf{A})^{-1}$ is the total requirement matrix. Entry ji shows the dollar value of the production of industry j that is required, both directly and indirectly, to deliver one dollar of the domestically produced commodity i to final uses. Note that in this matrix, rows are associated with industries and columns with commodities. Finally, we combine the \mathbf{TR} matrix with the final expenditure vectors \mathbf{e}_C , \mathbf{e}_X , \mathbf{e}_E to obtain

$$\begin{aligned}\mathbf{VA}_X &= \langle \mathbf{v} \rangle \mathbf{TR} \mathbf{e}_I, \\ \mathbf{VA}_C &= \langle \mathbf{v} \rangle \mathbf{TR} \mathbf{e}_C, \\ \mathbf{VA}_E &= \langle \mathbf{v} \rangle \mathbf{TR} \mathbf{e}_X,\end{aligned}\tag{B.1}$$

where the $(n \times n)$ matrix $\langle \mathbf{v} \rangle$ is a diagonal matrix with the vector \mathbf{v} in its diagonal. The vector \mathbf{v} contains the ratio of value added to gross output for each sector n . \mathbf{VA}_X , \mathbf{VA}_C , and \mathbf{VA}_E are our main objects of interest. They contain the sectoral composition of value added used for investment, consumption, and exports. To compute the shares, we simply divide each element by the sum of all elements in each vector:

$$\begin{aligned}\frac{\mathbf{VA}_i^x}{\mathbf{VA}^x} &= \frac{\mathbf{VA}_X(i)}{\sum_{i=1}^n \mathbf{VA}_X(i)}, \\ \frac{\mathbf{VA}_i^c}{\mathbf{VA}^c} &= \frac{\mathbf{VA}_C(i)}{\sum_{i=1}^n \mathbf{VA}_C(i)}, \\ \frac{\mathbf{VA}_i^e}{\mathbf{VA}^e} &= \frac{\mathbf{VA}_E(i)}{\sum_{i=1}^n \mathbf{VA}_E(i)}.\end{aligned}\tag{B.2}$$

B.2. Aggregation

We start with four national accounts identities. First, from the expenditure side, GDP can be obtained as the sum of expenditure in investment X , consumption C , exports E , minus imports M :

$$\text{GDP} = X + C + E - M.\tag{B.3}$$

Second, from the production side, GDP can be obtained as the sum of value added \mathbf{VA}_i produced in different sectors i :

$$\text{GDP} = \sum_i \mathbf{VA}_i.$$

Third, the value added of sector i can be expressed as

$$\mathbf{VA}_i = \mathbf{VA}_i^x + \mathbf{VA}_i^c + \mathbf{VA}_i^e,\tag{B.4}$$

where \mathbf{VA}_i^x , \mathbf{VA}_i^c , and \mathbf{VA}_i^e are the valued added produced in sector i used for final investment, final consumption, and final exports, respectively, and are obtained from equations (B.1) above. Note that summing up equation (B.4) across sectors gives us

$$\text{GDP} = \mathbf{VA}^x + \mathbf{VA}^c + \mathbf{VA}^e.$$

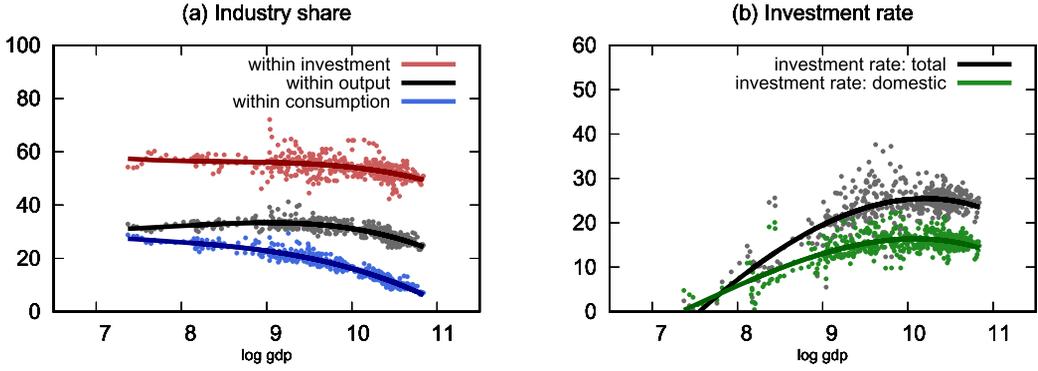


FIGURE B.1.—Sectoral shares for Industry and investment rate, within-country evidence. *Note:* Sectoral shares and investment rates from WIOD (dots) and projections on a low-order polynomial of log GDP per capita in constant international dollars (lines). The data are plotted net of country fixed effects.

And fourth, the expenditure in investment X (or analogously, consumption C and exports E) equals the sum of value added domestically produced that is used for investment VA^x and the imported value added that is used for investment (either directly or indirectly through intermediate goods), M^x :

$$X = VA^x + M^x, \quad (\text{B.5})$$

$$C = VA^c + M^c, \quad (\text{B.6})$$

$$E = VA^e + M^e. \quad (\text{B.7})$$

Note that summing equations (B.5)–(B.7) gives us equation (B.3) as $M = M^x + M^c + M^e$.

With these elements in place, note that the value added share of sector i in GDP can be expressed as

$$\frac{VA_i}{GDP} = \left(\frac{VA^x}{GDP} \right) \left(\frac{VA_i^x}{VA^x} \right) + \left(\frac{VA^c}{GDP} \right) \left(\frac{VA_i^c}{VA^c} \right) + \left(\frac{VA^e}{GDP} \right) \left(\frac{VA_i^e}{VA^e} \right). \quad (\text{B.8})$$

That is, the value added share of sector i in GDP is a weighted average of the value added share of sector i within investment $\frac{VA_i^x}{VA^x}$, consumption $\frac{VA_i^c}{VA^c}$, and exports $\frac{VA_i^e}{VA^e}$. These terms are the ones we have built in Appendix B.1 and that we describe in Table I and Panels (a), (c), and (e) of Figure 2. The weights are the share of domestic value added that is used for investment $\frac{VA^x}{GDP}$, for consumption $\frac{VA^c}{GDP}$, and for exports $\frac{VA^e}{GDP}$. Note that these weights are not the investment $\frac{X}{GDP}$, consumption $\frac{C}{GDP}$, and export $\frac{E}{GDP}$ rates as commonly measured in National Accounts because not all the expenditure in final investment, final consumption, and final exports comes from domestically produced value added. In particular,

$$\frac{VA^x}{GDP} = \left(\frac{X}{GDP} \right) \left(\frac{VA^x}{X} \right),$$

$$\frac{VA^c}{GDP} = \left(\frac{C}{GDP} \right) \left(\frac{VA^c}{C} \right),$$

$$\frac{VA^e}{GDP} = \left(\frac{E}{GDP} \right) \left(\frac{VA^e}{E} \right),$$

where the terms $\frac{VA^x}{X}$, $\frac{VA^c}{C}$, $\frac{VA^e}{E}$ denote the fraction of total expenditure in investment, consumption, and exports that is actually produced domestically, and which according to equations (B.5)–(B.7) must be weakly smaller than 1. Finally, note that in a closed economy, the terms $\frac{VA^x}{X}$, $\frac{VA^c}{C}$, $\frac{VA^e}{E}$ will equal 1e by construction and hence equation (B.8) would become

$$\frac{VA_i}{GDP} = \left(\frac{X}{GDP} \right) \left(\frac{VA_i^x}{VA^x} \right) + \left(\frac{C}{GDP} \right) \left(\frac{VA_i^c}{VA^c} \right). \quad (\text{B.9})$$

Equation (B.9) corresponds to equation (20) in the model.

APPENDIX C: FILTERING AND PROJECTING THE PANEL DATA

Dots and Thick Dark Lines in Figures. The thick dark lines in Figure 1, Figure 2, and Panels (b) and (c) in Figure 6 have been built as follows. First, we regress the desired variable z_{it} on a low-order polynomial of $\log y_{it}$ and country fixed effects α_{zi} :

$$z_{it} = \alpha_{zi} + \alpha_{z1} \log y_{it} + \alpha_{z2} (\log y_{it})^2 + \alpha_{z3} (\log y_{it})^3 + \varepsilon_{zit}, \quad (\text{C.1})$$

and next we use the prediction equation,

$$\hat{z}_{it} = \alpha_z + \hat{\alpha}_{z1} \log y_{it} + \hat{\alpha}_{z2} (\log y_{it})^2 + \hat{\alpha}_{z3} (\log y_{it})^3, \quad (\text{C.2})$$

with the arbitrary α_z intercept equal to the unweighted average of country fixed effects α_{zi} . The \hat{z}_{it} form the thick dark lines in the figures, while the clouds of points in these same figures are obtained by adding the estimated error $\hat{\varepsilon}_{zit}$ from regression equation (C.1) to the predicted series \hat{z}_{it} .

Data for the Estimation of the Demand System. We use the $\hat{z}_{it} + \hat{\varepsilon}_{zit}$ obtained from (C.1) and (C.2) as our data points. Note that this is analogous to using the actual data filtered from country fixed effects, that is, the differences between the data and the country means.

Data for the Calibration of the Dynamic Side of the Model. For the calibration of the dynamic side of the model, we first want to create time series for a synthetic country that follows a stylized process of development extracted from our panel data set. We proceed as follows:

1. Obtain the prediction functions for the variables of interest with regression (C.1).
2. Do the same for the growth of per capita GDP:

$$\Delta \log y_{it+1} = \alpha_{yi} + \sum_{p=1}^P \alpha_{yp} (\log y_{it})^p + \varepsilon_{yit}.$$

3. Create a time series for GDP per capita:
 - (a) Initialize the synthetic country: $\hat{y}_0 = \min\{y_{it}\}$.
 - (b) Fill the whole time series for \hat{y}_t between $t = 1$ and T using

$$\Delta \log \hat{y}_{t+1} = \alpha_y + \sum_{p=1}^P \hat{\alpha}_{yp} (\log \hat{y}_{it})^p,$$

where $\hat{\alpha}_{y1}$, $\hat{\alpha}_{y2}$, and $\hat{\alpha}_{y3}$ are the estimated values and α_y is an arbitrary intercept that we choose such that $\Delta \log \hat{y}_T = 0.02$, which is arguably the long-run rate of

growth of the U.S. economy, which we see as the economy at the technology frontier. T is determined by the number of periods it takes the synthetic country to reach the maximum income per capita in our panel, that is, T is the maximum s such that $\hat{y}_s \leq \max\{y_{it}\}$. In our exercise, we find $T = 96$.

4. Create the time series for the variables of interest \hat{z}_t between $t = 0$ and T using

$$\hat{z}_t = \alpha_z + \sum_{p=1}^P \hat{\alpha}_{zp} (\log \hat{y}_t)^p,$$

where $\hat{\alpha}_{z1}$, $\hat{\alpha}_{z2}$, and $\hat{\alpha}_{z3}$ are the estimated values in equation (C.1), and α_z is an arbitrary intercept equal to the unweighted average of all the country fixed effects $\hat{\alpha}_{zi}$.

APPENDIX D: ESTIMATION DETAILS

D.1. Two-Sample GMM Estimation

Our demand system consists of the following equations for $i = m, s$:

$$\frac{p_{it}c_{it}}{\sum_{j=a,m,s} p_{jt}c_{jt}} = g_i^c(\Theta^c; P_t, \sum_{j=\{a,m,s\}} p_{jt}c_{jt}) + \varepsilon_{it}^c, \quad (\text{D.1})$$

$$\frac{p_{it}x_{it}}{p_{xt}x_t} = g_i^x(\Theta^x; P_t) + \varepsilon_{it}^x, \quad (\text{D.2})$$

$$\frac{p_{it}y_{it}}{y_t} = g_i^x(\Theta^x; P_t) \frac{p_{xt}x_t}{y_t} + g_i^c(\Theta^c; P_t, \sum_j p_{jt}c_{jt}) \left(1 - \frac{p_{xt}x_t}{y_t}\right) + \varepsilon_{it}^y. \quad (\text{D.3})$$

To estimate the parameters of the model in (D.1)–(D.3), we use two different samples: (i) input-output data from the WIOD database to estimate equations (D.1)–(D.2) and (ii) aggregate data from the WDI-G10S database to estimate equation (D.3). Note that the model in (D.1)–(D.3) is an overidentified model with more moment conditions than parameters. Using the WIOD database, we can construct sample analogs of the following moment conditions for $i = m, s$:

$$E \left[\frac{\partial g_i^c}{\partial \Theta^c} \varepsilon_{it}^c \right] = 0, \quad (\text{D.4})$$

$$E \left[\frac{\partial g_i^x}{\partial \Theta^x} \varepsilon_{it}^x \right] = 0. \quad (\text{D.5})$$

The moment conditions in (D.4)–(D.5) correspond to the moment conditions exploited by a nonlinear OLS estimation of equations (D.1)–(D.2). In fact, estimating the parameters in Θ^c using a GMM estimator that optimally combines moments (D.4) using as a weighting matrix the variance-covariance matrix of these moments, coincides with the nonlinear SUR estimator in Herrendorf, Rogerson, and Valentinyi (2013). Analogously, we can use the moment conditions in (D.5) to estimate Θ^x .

Using the data from the WDI-G10S sample, we can construct sample analogs of the following moment conditions for $i = m, s$:

$$E \left[\frac{\partial g_i^c}{\partial \Theta^c} \left(1 - \frac{p_{xt} x_t}{y_t} \right) \varepsilon_{it}^y \right] = 0, \quad (\text{D.6})$$

$$E \left[\frac{\partial g_i^x}{\partial \Theta^x} \left(\frac{p_{xt} x_t}{y_t} \right) \varepsilon_{it}^y \right] = 0. \quad (\text{D.7})$$

The moment conditions in (D.6)–(D.7) correspond to the moment conditions exploited by a nonlinear OLS estimation of equation (D.3).

We combine our two samples to jointly estimate the entire system in (D.1)–(D.3). Our GMM estimator uses the two sets of moment conditions in (D.4)–(D.5) and (D.6)–(D.7) and combines them using as the weighting matrix the variance-covariance matrix of the moments. The measurement errors in equations (D.1)–(D.3) are allowed to be correlated within databases but uncorrelated across databases (since WIOD and WDI-G10S are independent databases). The GMM estimator that optimally combines the moment conditions in (D.4)–(D.7) is equivalent to a multivariate nonlinear regression of the system in (D.1)–(D.3) using the optimal instruments. We can express equations (D.1)–(D.3) in a compact notation:

$$Y_t = g_t(\theta) + \varepsilon_t,$$

where Y_t , $g_t(\theta)$, and ε_t are 6×1 vectors. The optimal instruments Z^* of the multivariate nonlinear regression in (15) are

$$Z^* = \Omega^{-1} \frac{\partial g_t}{\partial \theta},$$

where $\Omega = E(\varepsilon_t \varepsilon_t')$. This leads to the following optimal IV moment condition:

$$E \left[\left(\frac{\partial g_t}{\partial \theta} \right)' \Omega^{-1} \varepsilon_t \right] = 0;$$

a feasible estimator replaces Ω by an estimated variance matrix $\hat{\Omega} = \sum_t \hat{\varepsilon}_t \hat{\varepsilon}_t'$.

D.2. Income Elasticity

Our demand system generates nice closed-form solutions for the expenditure elasticity of each good. In particular, it can be shown that

$$\left[\frac{d \left(p_{it} c_{it} / \sum_j p_{jt} c_{jt} \right)}{d \sum_j p_{jt} c_{jt}} \right] \left[\frac{\sum_j p_{jt} c_{jt}}{\left(p_{it} c_{it} / \sum_j p_{jt} c_{jt} \right)} \right] = \frac{\bar{c}_i}{c_{it}} - \theta_i^c \left(\frac{p_{ct}}{p_{it}} \right)^{\frac{\rho_c}{1-\rho_c}} \left(\frac{\sum_j p_{jt} \bar{c}_j}{p_{it} c_{it}} \right).$$

When all \bar{c}_i are zero, the demand system is homothetic: the expenditure shares do not change with total expenditure. Luxury goods (necessities) display a positive (negative) expenditure elasticity. Note that it is not a necessary condition to have $\bar{c}_a < 0$ for agriculture good to be necessity, as the second term in the r.h.s. can be positive and larger in absolute value than \bar{c}_a .

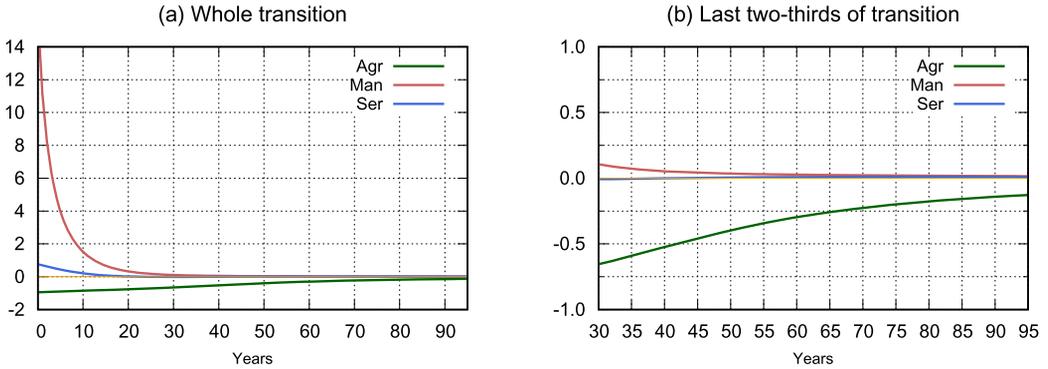


FIGURE D.1.—Expenditure elasticities.

In Figure D.1, we report the expenditure elasticities implied by our estimates. We see how agriculture is a necessity and both manufacturing and services are luxury goods. This is especially important at early stages of development because as the economies become richer, the \bar{c}_i vanish relative to c_{it} and relative to total expenditure. Note that the expenditure elasticity is larger for manufactures than for services during the early stage of development.

D.3. *Alternative Demand Systems*

The literature of structural change has typically assumed that either the aggregators for consumption and investment are the same or that the investment goods are only produced with manufacturing value added. The former case eliminates the extensive margin of structural change, while the latter case exaggerates it. In this appendix, we estimate restricted versions of our aggregators and show their consequences for structural change. First, consistently with [Acemoglu and Guerrieri \(2008\)](#), we remove the income effects ($\bar{c}_i = 0 \forall i$) and impose that the investment and consumption aggregators are the same (Model a.1). This formulation has no income effect, so it is very hard for it to match the evolution of the sectoral composition of GDP. For this reason, we consider a second model where the income effects in consumption are present but the remaining parameters of the investment and consumption aggregators are the same. In this formulation, consumption and investment have the same sectoral composition at the end of the development process (when the \bar{c}_i are quantitatively irrelevant) but not at early stages (Model a.2). And third, we consider the case in which the sectoral composition of investment is 100% manufacturing and the consumption aggregator is as in the benchmark model (Model b). This would be analogous to the formulation in [Kongsamut, Rebelo, and Xie \(2001\)](#), while [Ngai and Pissarides \(2007\)](#) further assumed $\bar{c}_i = 0$. We estimate these alternative demand systems with equation (25) only, while imposing the constraints $\bar{c}_i = 0$, $\theta_i^x = \theta_i^c$, and $\rho_x = \rho_c$ in the first case, $\theta_i^x = \theta_i^c$ and $\rho_x = \rho_c$ in the second case, and $\theta_a^x = \theta_s^x = 0$ and $\theta_m^x = 1$ in the third case.

Fitting the Sectoral Composition of GDP. Figures D.2, D.3, and D.4 show how these different demand systems fit the data. Model (a.1) cannot match the hump-shaped evolution of manufacturing in GDP; see Panel (f) in Figure D.2. As a consequence, it also produces a poor match of the agricultural share; see Panel (b). This is interesting. In principle, a model with only relative price changes and no income effects can generate a hump

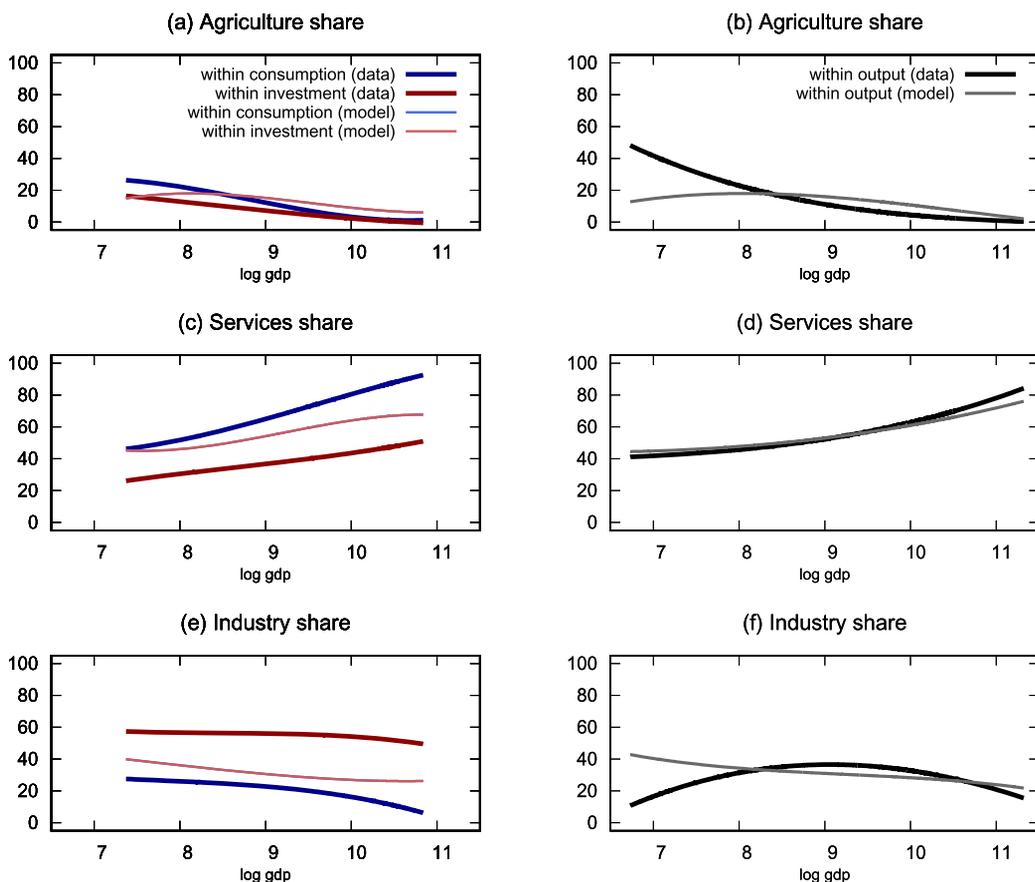


FIGURE D.2.—Model fit, sectoral composition. Model (a.1). *Note:* See footnote in Figure 4.

in manufacturing if the rate of growth of prices in manufacturing is in between the ones of agriculture and services (see [Ngai and Pissarides \(2007\)](#)). What this example shows is that, given the observed evolution of relative sectoral prices, this does not happen. Next, models (a.2) and (b) can fit the data on sectoral evolution of GDP quite well; see Panels (b), (d), (f) in Figures D.3 and D.4.

Fitting the Sectoral Composition of Consumption and Investment. All three models, however, grossly mismatch the sectoral composition of consumption and investment; see Panels (a), (c), (e) in the three figures. This means that these three models will misrepresent the extensive margin of structural change. For instance, looking at Panel (e) in the three figures, we see how: Model (a.1) has no role for the extensive margin, that is, the sectoral composition of investment and consumption are the same (the thin blue line perfectly overlaps with its red counterpart and therefore is hidden); Model (a.2) allows for some action in the extensive margin at early stages of development (the sectoral composition of investment and consumption are different from each other at early stages of development, but less than in the data); and Model (b) exaggerates the extensive margin (the asymmetry in the sectoral composition of investment and consumption is much larger than in the data).

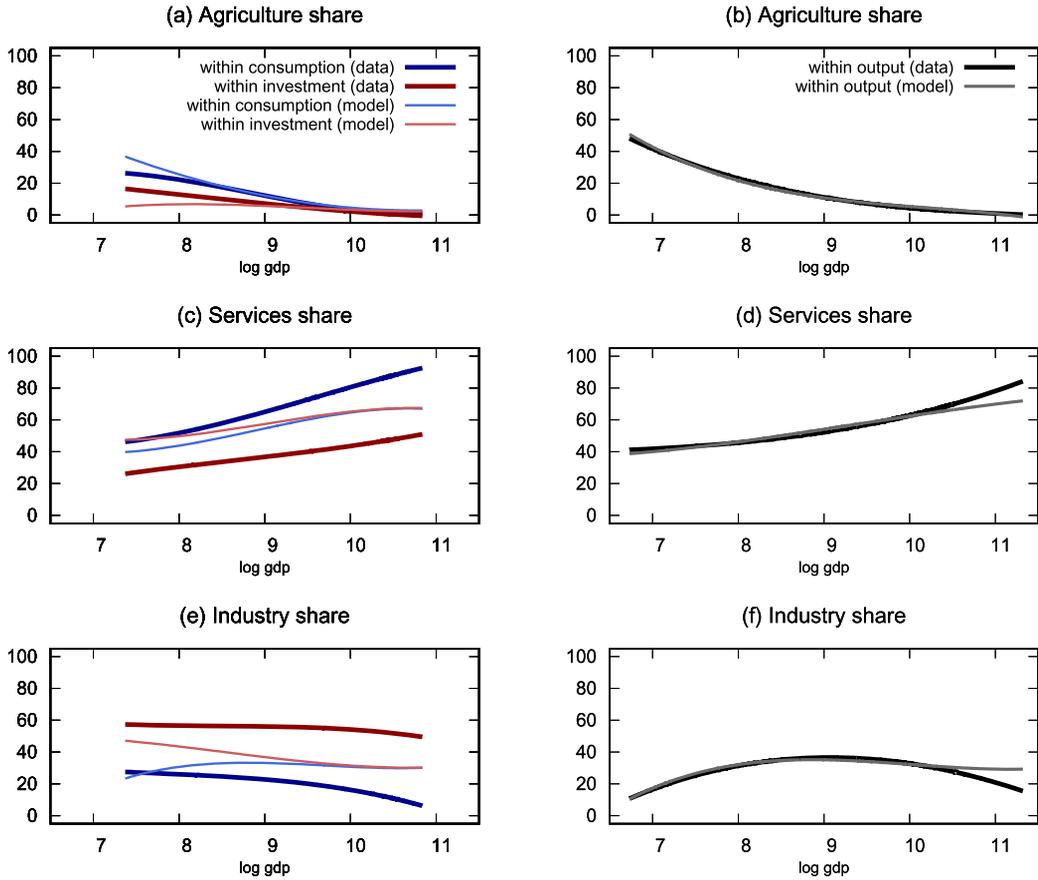


FIGURE D.3.—Model fit, sectoral composition. Model (a.2). *Note:* See footnote in Figure 4.

Decomposition of Forces Driving Structural Change. In order to understand how these models manage to fit the sectoral composition of GDP, we perform the same types of counterfactuals with the demand system as in Section 5.3 in the paper. Panel (a) in Figure D.5 plots the estimated and counterfactual manufacturing shares of GDP for the demand system estimated in the paper (this represents a reprint of Panel (c) in Figure 5). The other panels in Figure D.5 plot the same objects for the three demand systems considered here: Model (a.1), Model (a.2), and Model (b). We clearly see that Model (a.1) does not generate any sectoral reallocation through the extensive margin (as sectoral shares of investment and consumption are identical). Structural change only happens through the intensive margin, and in particular through price effects because the \bar{c}_i are set to zero. For this reason, this model cannot match the sectoral evolution of manufacturing. Next, Model (a.2) does generate some but not much action through the extensive margin (thick yellow line): it explains a 2 percentage points increase and a 1 percentage point decline of manufactures (compared to 11 p.p. increase and 6 p.p. decline in the benchmark model). This is because, as shown in Panel (e) in Figure D.3, the manufacturing shares of consumption and investment are very similar. In this model, the income effect (thin blue line) is stronger than in the benchmark: it generates an increase in manufacturing of 44.3 p.p. (compared to 37 p.p. in the benchmark). This happens because, given the small trac-

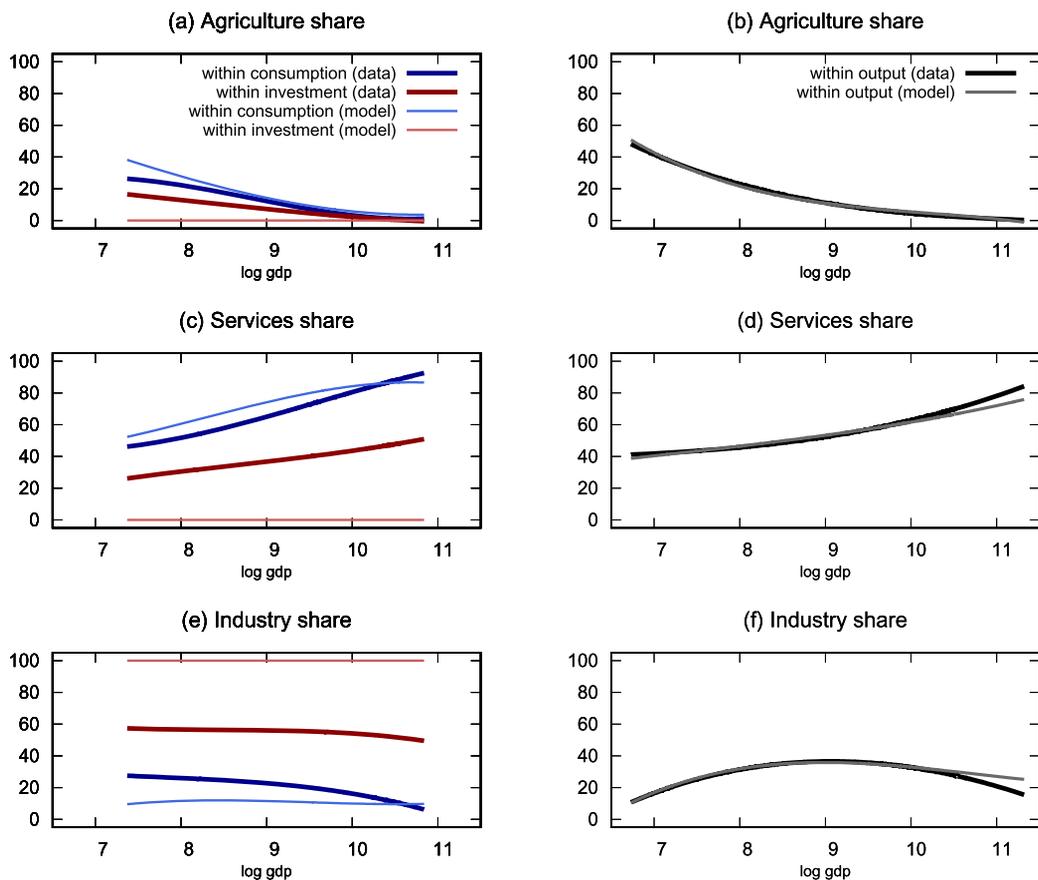


FIGURE D.4.—Model fit, sectoral composition. Model (b). *Note:* See footnote in Figure 4.

tion of the extensive margin, the income effect must do the weight lifting for the initial increase in manufacturing. Finally, in Model (b), the extensive margin becomes very important (an 18 p.p. increase and a 10 p.p. decline of manufactures) and explains almost all the hump in manufacturing found in the data (a 22 p.p. increase and a 10 p.p. decline). This happens because the sectoral asymmetry between consumption and investment is counterfactually large. Additionally, this makes the income effect much less important than in the benchmark case as the initial increase in manufacturing is taken care by the extensive margin: the income effect only generates a 16 p.p. increase in manufacturing (compared to the 37 p.p. in the benchmark).

Consequences for the Dynamic System. Given the estimated demand systems, we can calibrate the dynamic side of the model as we did in Section 5.4. That is, we obtain the new series for the exogenous productivity processes and for the investment wedge. The sectoral productivity terms, B_{it} , are unchanged because they depend on relative prices only. The common productivity term, $B_{ct}B_t^{1-\alpha}$, is unchanged because both output and investment expenditure data (which are used to build the capital stock) are unchanged. Next, investment-specific technical change, χ_t , does change across models; see Figure D.6. The relative investment price data are the same in all models but the productivity aggregators

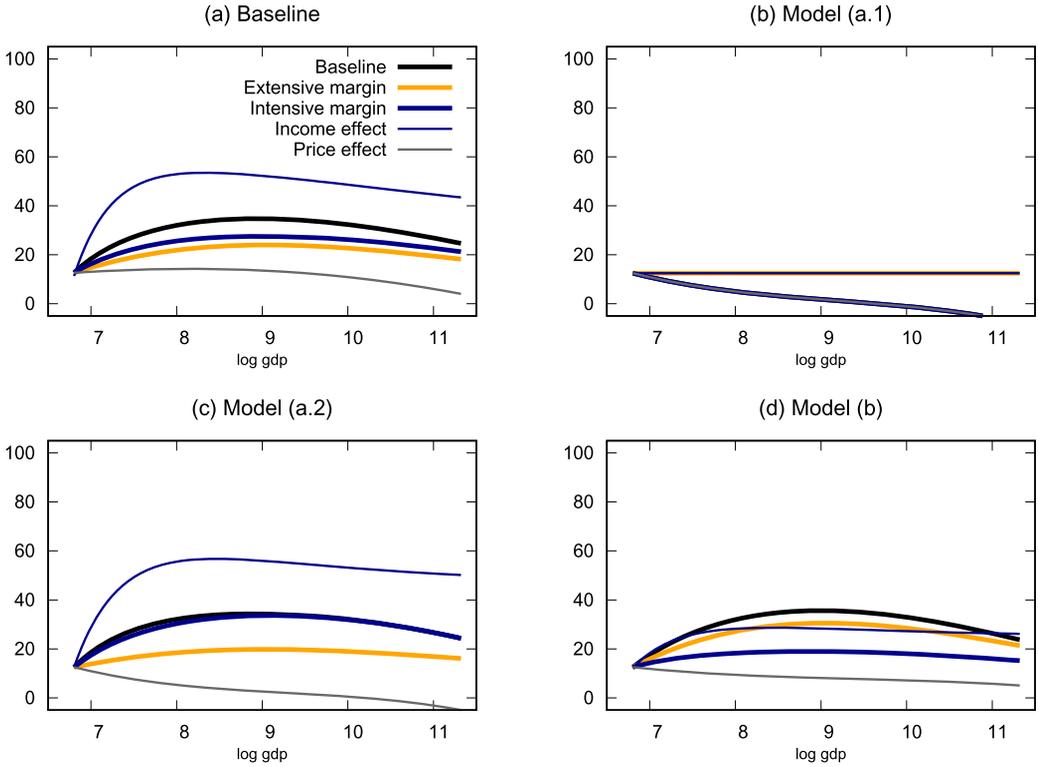


FIGURE D.5.—Sectoral composition of Industry: counterfactual exercises. *Note:* Estimated and counterfactual shares of manufacturing according to different demand systems. See footnote in Figure 5.

B_{xt} and B_{ct} change with the different demand systems. In particular, B_{xt} and B_{ct} are equal to each other in models (a.1) and (a.2). Hence, in these two models, χ_t absorbs all the evolution of the relative price of investment: absent the growth in B_{xt}/B_{ct} due to the relative increase in B_{mt}/B_{st} , χ_t has to grow more. Instead, in Model (b), B_{xt}/B_{ct} grows at a faster rate than in the benchmark model due to the excessive weight of manufactures within investment. This means that during the first half of the development process, $1/\chi_t$ grows at a faster rate than in the benchmark in order to match the nearly constant p_{xt}/p_{ct} , while during the second half $1/\chi_t$ is nearly constant. Finally, the investment wedge obtained in each model is different. This is shown in Panel (d) of Figure D.6. In the case of Model (a.1), we find an initial wedge somewhat lower than in the benchmark. The reason for this is that Model (a.1) restricts $\bar{c}_i = 0 \forall i = a, m, s$. In our benchmark model, \bar{c}_m and \bar{c}_s are large and positive, while \bar{c}_a is small and negative. This implies that, at early stages of development, the consumption basket c_t is smaller (through a lower consumption endowment given by the \bar{c}_i), and grows more with consumption expenditure in Model (a.1) than in the benchmark model; see equation (4). Therefore, because the growth of the consumption basket in the left-hand side of the Euler equation is larger in Model (a.1) than in the benchmark model, a lower investment wedge is needed for the model to be consistent with the data (and in particular, with a large marginal product of capital). Yet, the differences are not large and the shapes are very similar. Models (a.1) and (b) do not restrict $\bar{c}_i = 0$ and the differences in the inferred intertemporal wedges are negligible.

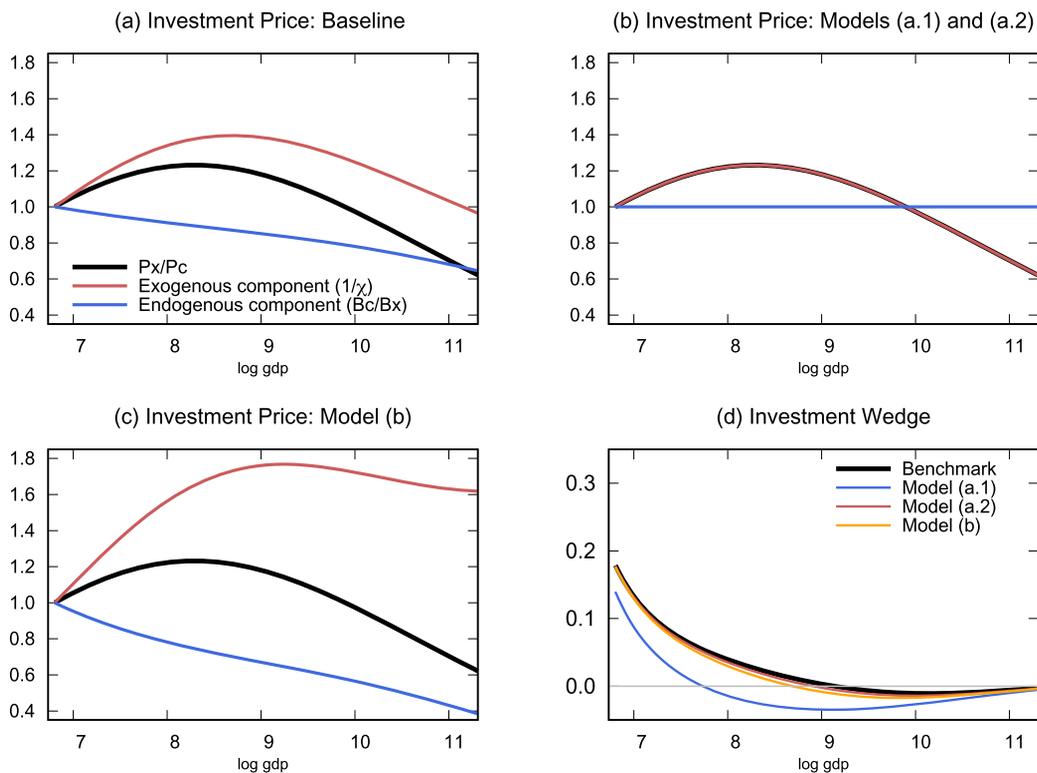


FIGURE D.6.—Exogenous series. *Note:* Panels (a)–(c): Relative investment price (black line) decomposed into its exogenous (red line) and endogenous (blue line) components. Panel (d): Investment wedge τ_t for the benchmark calibration and for the calibrations with the alternative demand systems.

Hence, the need of an intertemporal wedge to fit the investment data is robust to the intratemporal distortions across sectors.

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Co-editor Fabrizio Zilibotti handled this manuscript.

Manuscript received 26 April, 2018; final version accepted 7 March, 2021; available online 14 May, 2021.