Sources of Growth in an Empirical Dual Economy Model*

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Abstract: While empirical investigation of dual economy models has long been in the shadow of the cross-country growth literature analysed at the aggregate level, recent work has refocused the attention on the importance of accounting for sectoral structure in the analysis of growth and development. In this study I revisit the theoretical and empirical literatures for dual economy models and investigate the barriers to structural change within a flexible regression framework which allows for technology heterogeneity across sectors and countries as well as highly idiosyncratic productivity evolution. Employing data from a panel of developing and developed countries over three decades I focus on the relative importance of TFP growth differences, TFP levels differences and factor misallocation between sectors for aggregate development, using counterfactual exercises adapted for our empirical setup. My findings challenge some of the conventional wisdom in the dual economy literature.

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1 Introduction

Much of the early work on economic growth modeling proceeded without close connection to observed data. The models were in Solow's classic exposition of growth theory inspired by stylized 'Kaldor' facts (Kaldor, 1957). Dual economy models of structural transformation (Lewis, 1954; Jorgensen, 1961; Kaldor, 1966; Kuznets, 1961; Ranis and Fei, 1961; Robinson, 1971), which represent the original core literature on economic development in "backward" economies (Jorgensen, 1961, p.309) as opposed to the analysis of aggregate growth in developed economies (e.g. Solow, 1956, 1957; Swan, 1956), used case studies (e.g. Paauw and Fei, 1973) and facts at least as stylized as those in the Solow-Swan growth context. Empirical studies employed a vast array of explanatory variables of growth, while methodological, statistical, and conceptual difficulties on top of sample heterogeneity made it difficult to draw reliable conclusions from the existing literature (Levine and Renelt, 1991). The key papers which brought modeling and data together were the contributions of Barro (1991) and Mankiw et al. (1992), which initiated a major revival in the Solow-Swan model and effectively merged the concerns of economic development with those of aggregate growth, with any dual economy aspects of development largely ignored. The literature begun in the early 1990s has yielded a large array of models (see Aghion and Howitt, 1998; Durlauf and Quah, 1999; Easterly, 2002; Durlauf et al., 2005) and cross-country analysis continues to be dominated by an empirical version of the aggregate Solow-Swan model (Temple, 2005) with much of the debate focusing on the relative importance of factor accumulation versus TFP (Young, 1995; Klenow and Rodriguez-Clare, 1997a,b; Easterly and Levine, 2001; Hsieh and Klenow, 2010).

While there is recent research using a dual economy model framework or emphasizing the importance of accounting for sectoral structure in the analysis of economic development (e.g. Vollrath, 2009a,b; Duarte and Restuccia, 2010; Alvarez-Cuadrado and Poschke, 2011; Vollrath, 2011; Eberhardt and Teal, 2013; Eberhardt and Vollrath, 2018), this approach is still largely absent from textbooks on economic growth and has not been the central focus of attention for most empirical work (Temple, 2005). A primary reason for this neglect has been the availability of data. The Penn World Table (PWT) dataset (Feenstra et al., 2015) and the Barro-Lee data on human capital (Barro and Lee, 2013) have supplied macro-data which ensure that the aggregate Solow-Swan model can be readily estimated. Much of the most recent empirical work on dual economy models has been confined to the single cross-section or single country setup (e.g. Bustos et al., 2016; Emerick, 2018; Alvarez, 2020; Bustos et al., 2020), which raises questions for robustness and external validity. In this paper I return to the cross-country setup and exploit the efforts of a team of researchers at the World Bank who developed a unique comparable panel data for agriculture and manufacturing (Crego et al., 1998), including comparable sectoral capital stock data, which allow for a close match between theoretical models and the data.

A common feature across early theoretical and empirical literatures on economic development and growth was the use of closed economy models. The basic models put forward by Arthur Lewis (Lewis, 1954) and Solow-Swan (Solow, 1956, 1957; Swan, 1956) were closed economy models. However, it was soon realized that these were not the most appropriate models for economies which were small in geographical size and open to the world economy in the sense that their influence on the prices of their products was minimal. As noted by Lucas (1988), the theory of trade as developed by Ricardo and Heckscher-Ohlin implies that trade can have "a level effect, analogous to the one-time shifting upward in production possibilities, [but] not a growth effect" (12) on income. The strong correlation apparent in the data between income growth and trade led to much new work on the theory of how trade may impact growth (e.g. Grossman and Helpman, 1991; Rivera-Batiz and Romer, 1991; Aghion and Howitt, 1992; Matsuyama, 1992), one key mechanism being via improvements in technical progress, another being through spillovers. Much of the empirical work on this topic (e.g. Coe et al., 1997; Frankel and Romer, 1999; Dollar and Kraay, 2004) used reduced form models at the aggregate economy level and side-stepped the theoretical issues and mechanisms as to exactly why more open economies might grow faster. Matsuyama (2009) lamented the apparent mismatch between the theoretical and empirical literature on structural change, whereby "[m]ost empirical studies of structural change... write down a closed economy model, apply it to each country, and use the cross-country data to test the model... under the false assumption that each country offers an independent observation" (478).

The first contribution of this paper is to provide a direct response to the Matsuyama (2009) critique. My empirical approach recognizes that countries operate in a global economy where economies are interdependent, employing a common factor framework (Pesaran, 2006; Bai, 2009), which allows me to model unobserved TFP alongside global shocks, such as the 1970s oil crises, which have affected different countries in different ways. The resulting 'cross-section correlation' in the data represents the form of interdependence Matsuyama (2009) argues is currently missing from the analysis.[1] This empirical approach will be able to consistently estimate sectoral production function parameters (production technology) in the presence of time-varying unobserved heterogeneity (TFP), which is correlated with the observed inputs to production (endogeneity).

The second contribution of this study is to investigate the sources of growth in an empirical dual economy model which allows for cross-country technology heterogeneity. Previous work on agricultural and manufacturing production (Eberhardt and Teal, 2013) showed that the assumption of common technology coefficients (output elasticities with respect to labour and capital) across countries within these broad economic sectors is rejected by the data . Motivated by the 'new growth' (Murphy et al., 1989; Banerjee and Newman, 1993) and 'ap-

[1] Note that standard panel estimators commonly applied in cross-country analysis, e.g. fixed effects, IV or GMM estimators (Arellano and Bond, 1991; Blundell and Bond, 1998), assume cross-section independence.

propriate technology' literatures (Basu and Weil, 1998) as well as a theoretical model developed in Mundlak (1988) and Mundlak et al. (2012) we specified country-sector specific technology coefficients and found that the data were much more in line with this notion of heterogeneous technology across countries. Our primary focus in this earlier work was to highlight the importance of accounting for sectoral differences as well as cross-section dependence when investigating growth and development in countries undergoing structural change, and to show that aggregate economy analysis in this context yields highly misleading results with serious implications for standard growth or development accounting. This analysis was possible due to the availability of comparable panel data for agriculture and manufacturing (Crego et al., 1998) that allow a closer matching between theoretical models and the data, which I further exploit in the present paper: I revisit the large literature on dual economy models and, within a heterogeneous technology framework, provide empirical analysis for the various hypothesized drivers of structural change, including TFP level or TFP growth differences between sectors as well as marginal factor product duality.

My results suggest that a flexible empirical dual economy model points to a more significant role in economic development for factor accumulation relative to TFP growth, that TFP growth in agriculture is not systematically larger than in manufacturing, that TFP level differences between sectors show significant variation across countries, and that marginal factor duality is an important feature of the economies in my sample. The insight that factor input variation, in combination with factor market duality, is driving the development process echoes and extends the work of Vollrath (2011) and challenges the results in Caselli (2005). Furthermore, the conclusions of Martin and Mitra (2002), who found that agricultural productivity growth systematically exceeded that in the manufacturing sector, are qualified significantly.

The remainder of this paper is organized as follows: Section 2 provides an encompassing conceptual framework for the analysis of dual economy effects at the macro level and reviews the existing literature. In section 3 I introduce an empirical specification of my dual economy framework, discuss the data and review the empirical implementation. Section 4 briefly reports production function results; I then investigate suggested sources of growth and development empirically in Section 5. Section 6 summarizes and concludes.

2 Growth and Development

The literature on dual economy models is surprisingly large, given the relatively limited impact this approach has had in entering textbooks on economic growth theory and analysis, and economics 'orthodoxy' in general (Temple, 2005). With the availability of sectoral data for a cross-section of countries limited until recently, some of the existing work in this area is built on models relatively disjoint from the formulation of empirically testable questions, while other studies have focused on very specific details of the growth and development process which are then tested using simulation or calibrated models. As a result, given their complexity and data requirements, many of the dual economy models do not suit themselves for empirical testing. In this section I present a theoretical dual economy model based on the existing literature, however focused on providing as general and encompassing a treatment as possible whilst formulating an empirically testable model. Findings from previous work using accounting exercises and a small number of sectoral production function estimations suggest a number of potential sources of growth in a dual economy framework which I review below.

2.1 A theoretical model of an open dual economy

The early literature on structural change did not pursue formal modeling of the small open dual economy setup, but limited itself to a conceptual understanding of the link between structural change and potential growth in a closed economy. Lewis (1954), Kaldor (1966), and Ranis and Fei (1961), for instance, all emphasize the potential for surplus labour in agriculture to act as a major driver for structural change via the migration of labour into the emerging manufacturing sector. In their analyses elastic labour supply enables economic growth by keeping wages in the modern sector low and preserving industrial peace (Temple, 2001; Temin, 2002; Barbier and Rauscher, 2007). A somewhat more complex analysis suggests that agricultural income and food supply constraints should be the focus of analysis, since they represent barriers to structural change and thus development (Jorgensen, 1961). Openness to trade, however, somewhat relaxes these constraints.

The supply side of a small, open dual economy can be represented by two sectors, assumed to be agriculture ('traditional sector') and manufacturing ('modern sector'), producing distinct goods. It is suggested that these two types of production are geographically distinct, the former present in rural areas and the latter in urban areas. Their respective technologies are assumed Cobb-Douglas but unrestricted with regard to returns to scale

$$
\begin{aligned}
Y_{at} &= A_{at}\, F(K_{at},\, L_{at},\, N_{a,t}) = A_{at} K_{at}^{\alpha}\, L_{at}^{\beta}\, N_{a,t}^{\gamma} \qquad \alpha, \beta, \gamma < 1 && (1)\\
Y_{mt} &= A_{mt}\, G(K_{mt},\, L_{mt}) = A_{mt} K_{mt}^{\phi}\, L_{mt}^{\psi} \qquad \phi, \psi < 1 && (2)\\
A_{jt} &= A_{j0}\, e^{\lambda_{jt}} \qquad \text{for } j = a, m && (3)
\end{aligned}
$$

where A represents technical efficiency of production (TFP),[2] K is physical, reproducible capital, and L is labour (either raw labour or adjusted for human capital differences) for both agricultural and manufacturing sectors a and m.[3] Capital and labour are stock variables which

[2] I see this as a 'catch-all' for disembodied levels of productive efficiency and technology as well as characteristics such as taxation, regulation, climate, soil conditions etc., following Gollin et al. (2002).

[3] Note that agricultural and rural labour should not be taken as homogeneous, but we can assume a setup that allows us to keep the model as it is laid out above, without losing the appeal of this notion (Temple, 2005): I assume human capital to be embodied partly within capital and partly within the technical progress term. Human capital data in Timmer (2002) would halve the number of countries in our manufacturing

can be accumulated infinitely, but are subject to diminishing returns. N is non-reproducible capital (assumed to be arable land and other forms of natural capital), and only enters the agricultural production function. Below I drop the time subscript for ease of exposition.

In the most general specification TFP growth rates λ and TFP levels A are allowed to differ across sectors, countries, and in case of TFP growth across time. When a country's manufacturing sector enjoys higher TFP growth than its agricultural sector, this implies *ceteris paribus* higher output growth in manufactured goods, and (deflated by sector share in total output s_a, s_m) higher aggregate output growth g.

$$g = \dot{Y}/Y = \dot{Z}/Z + \eta\dot{L}/L + \mu\dot{K}/K \Rightarrow \dot{Z}/Z = s_a\dot{A}_a/A_a + s_m\dot{A}_m/A_m. \tag{4}$$

Allowing TFP growth λ to vary over time allows for a more realistic dynamic evolution of the sectoral productivity level than a constant TFP growth rate. Given differential TFP levels between sectors, say $A_a < A_m$, structural transformation in the form of labour migration to manufacturing would result in a temporary level effect on output. Unlike in the TFP growth case this would not change the *perpetual* growth trajectory of the economy. Persistent and significant TFP level differences between sectors signal the presence of barriers to technology acquisition or some other form of friction in the low-TFP sector, while TFP level differences across countries signal frictions at the country-level (Caselli, 2005; Restuccia et al., 2008). I assume that the economy is open to trade in products but closed to cross-country factor migration such that

$$Y = Y_a + pY_m, \tag{5}$$

where the price of the agricultural good Y_a is the numeraire and p provides the relative price of manufactures, exogenously determined by the world price. I restrict discussion to incompletely specialized economies. Full capital employment

$$K = K_a + K_m, \tag{6}$$

with capital perfectly mobile between the two sectors leads to rental rate equalisation

$$r_a = \mathrm{MPK}_a = A_a\partial F/\partial K_a = \alpha\frac{Y_a}{K_a} \qquad r_m = \mathrm{MPK}_m = pA_m\partial G/\partial K_m = p\phi\frac{Y_m}{K_m} \qquad r_m = r_a. \tag{7}$$

The first-best equilibrium for the economy is defined by equations (1)-(3) and (5)-(7), in addition to equilibrium conditions in the labour market: under full employment and with wages equal to marginal products, workers will (freely) migrate between sectors until wages are equalised. However, in order to provide a specification as general as possible, I do not impose wage equalisation, but assume labour market disequilibrium in form of some exogenously-

dataset since only developing nations are discussed. A UNESCO dataset discussed in Córdoba and Ripoll (2009) contains only a handful of observations across time and countries.

determined wedge $0 < k < 1$ drives manufacturing wages *above* those in agriculture:[4]

$$w_a = \mathsf{MPL}_a = A_a \partial F/\partial L_a = \beta \frac{Y_a}{L_a} \quad w_m = \mathsf{MPL}_m = pA_m \partial G/\partial L_m = p\psi \frac{Y_m}{L_m} \quad w_a = k w_m. \tag{8}$$

Wage equalisation across sectors would provide the optimal output solution and it can be deduced that a wage differential between sectors leads to an equilibrium characterized by lower output. Adopting the Harris and Todaro (1970) approach to inter-sectoral labour market equilibrium, I assume unemployment in the urban labour market (L_u), such that

$$L = \underbrace{L_a}_{\text{rural}} + \underbrace{(L_m + L_u)}_{\text{urban}} \tag{9}$$

The key assumption in this approach is that in the presence of wage differentials and urban unemployment, rural (agricultural) migrants discount the urban wage, such that migration occurs until actual rural wage is equal to expected urban wage:[5]

$$w_a = \mathbb{E}[w_m] = (1 - u) w_m. \tag{10}$$

The expectation $\mathbb{E}[\cdot]$ of the urban wage is simply the probability of obtaining a job $(1 - u)$, which is determined by the urban unemployment rate

$$u = L_u/(L_m + L_u). \tag{11}$$

In analogy to the wage dualism developed here I relax the assumption of rental rate equalisation across sectors, replacing the parity condition in equation (7) with

$$r_a = h r_m \qquad h > 0 \tag{12}$$

Financial frictions and heterogeneous access to credit across locations (urban, rural) represent some reasons to motivate this setup. In the presence of rental rate dualism the equilibrium capital allocation will result in lower output than in the first-best solution. The resulting open economy Harris-Todaro model is represented by equations (1)-(3), (5)-(6), the labour market conditions (9)-(11), the rental rate condition (12) and the assumption that the manufacturing wage is exogenously fixed above the agricultural wage, while returns to capital can differ freely across sectors. Since this is a small open economy (with no taxes, tariffs or subsidies) and thus

[4] Temple (2005) suggests migration restrictions, or institutional reasons such as minimum wage legislation, trade unions, or an efficiency wage system in manufacturing as possible sources of this wage gap. Further, migration costs between sectors should be regarded as non-negligible. Additional considerations relate to the family organisation of asset returns (Ranis and Fei, 1961) whereby the wage in agriculture is equal to the average, rather than the marginal labour product which results in too little employment in the modern sector (Ranis and Fei, 1961; Robertson, 1999).

[5] Assuming risk-neutral agents who obtain no wage at all if unemployed.

all prices are fixed exogenously, the demand side and preferences need not enter the study of equilibrium in the economy (Temple, 2005; Córdoba and Ripoll, 2009). As will become clear, the above model encompasses the various modeling approaches taken in the existing literature on dual economy models.

2.2 A selective literature review of the sources of growth in dual economy models

This section provides an overview of the potential sources of growth in this class of models as developed in the relevant literature. I distinguish (a) differences in the *growth rate* of TFP between sectors, (b) differences in the *level* of TFP between sectors, and (c) marginal factor product dualism.

2.2.1 Differences in TFP growth rates across sectors: technical progress

In the early work on dual economy models and in development thinking in general, the manufacturing sector is commonly assumed to experience higher 'technical progress' than the agricultural sector (Lewis, 1954; Ranis and Fei, 1961; Prebisch, 1984)[6] — the Ricardian assumption of zero technical progress in agriculture represents the extremum of this view (Martin and Mitra, 2002). In the presence of higher TFP growth in manufacturing, migration of labour from agricultural to the manufacturing sector leads to increased aggregate output growth as sketched in the model above.[7]

A number of papers argue for differential TFP growth between sectors as a mechanism for structural change and economic development. Models by Martin and Mitra (2002) and Caselli and Coleman II (2001) assume differential capital coefficients and allow for TFP growth to vary across sectors, while abstracting from marginal factor dualism. Martin and Mitra (2002) use a general production function model focusing on the importance of technology and technical progress in agriculture. Using sectoral capital stock data from Crego et al. (1998) also adopted in this paper they employ two methods to derive TFP growth values for each country: firstly, they estimate sectoral CRS production functions[8] including country-specific intercept and trend terms (their empirical TFP growth estimates). Secondly, as a check on these esti-

[6] Greenwald and Stiglitz (2006) provide a strong rationale for higher innovation/technical progress in the formal manufacturing sector by drawing attention to its common characteristics: manufacturing firms are large, longlived, stable and geographically concentrated in comparison to most agricultural production units (usually the household). These factors translate into higher propensity for innovation due to (*inter alia*) higher returns on investment, human capital accumulation, improved knowledge diffusion, easier taxation and thus higher propensity for publicly funded innovation efforts.

[7] When countries however experience barriers to openness the importance of domestic food-production puts a premium on agricultural TFP growth (Irz and Roe, 2005) and labour movement into manufacturing is not always viable: economic growth is arrested without technical progress in agriculture fulfilling subsistence requirements (Jorgensen, 1961; Ranis and Fei, 1961; Matsuyama, 1992).

[8] They carry out estimations for both CD and translog forms (only coefficients for the former are reported).

mates, they carry out a standard TFP growth accounting exercise based on observed factor shares. Their production function estimations establish a significantly higher capital elasticity for manufacturing (.69) than for agriculture (.12). In order to justify this result they argue that the coefficient for manufacturing may capture part of the elasticity of output with respect to human capital, which is not included in the model.[9] Both the estimated TFP growth terms and those derived from the accounting exercise suggest higher technical progress in agriculture, a statistically significant result that holds across the vast majority of countries in their sample. Analysis of sectoral TFP levels suggests more rapid convergence in agriculture and further strengthens their conclusion that "a large agricultural sector. . . may be an advantage in terms of growth performance" (Martin and Mitra, 2002, p.418). These results are still widely cited as evidence against the Ricardian assumption of zero productivity growth in agriculture or the absence of learning-by-doing in this sector.

The model by Caselli and Coleman II (2001) imposes relatively faster TFP growth in agriculture, less than unit income elasticity in demand for agricultural goods, and a fall in the cost of non-agricultural sector skills acquisition to explain the link between structural change and regional convergence within the United States during 1880-1980. In their model both manufacturing and agricultural production functions contain land, labour and capital as factor inputs, while TFP levels are identical across regions in manufacturing but differ in agriculture, such that agriculture is only profitable in the South. Initial income levels are explained by the prevalence of agriculture across states. They calibrate this model with differential capital coefficients for the two sectors and an initial TFP growth rate for agriculture double that for manufacturing. The assumption of declining education costs is crucial for a good fit of the model's predictions with historical experience. As their simulation shows, productivity increases in agriculture allow for a reduction in the sector's employment, accompanied by a rise in nationwide relative agricultural wages.

2.2.2 Differences in TFP levels across sectors: technical efficiency

Differential efficiency levels between sectors in the general dual economy model outlined above suggest that labour migration to the sector with higher TFP level results in a temporary *level* effect on aggregate output. This effect is limited to the period when the economy is undergoing structural change, but nevertheless offers substantial welfare improvement (Temple, 2003; Caselli, 2005). The empirical literature on sectoral TFP level differences in their impact on aggregate growth is dominated by development accounting (Caselli, 2005; Restuccia et al., 2008) and calibrated simulation (Gollin et al., 2002; Restuccia, 2004) exercises. All of these abstract from rental rate dualism, while only Restuccia et al. (2008) consider wage dualism.

[9]The coefficient on land in agriculture is .24. All coefficients are statistically significant.

Caselli (2005) adopts a sectoral production framework containing human capital-augmented labour and capital in manufacturing, with land an additional factor input in agriculture.[10] He assumes marginal capital product equalisation across sectors of production. Following calibration, where differential capital coefficients in agriculture and manufacturing are imposed, he computes two sample statistics for a cross-section of countries: (i) a variance decomposition statistic, which indicates the share of sectoral output that can be explained by observed factor inputs; and (ii) an inter-percentile differential, which captures the same idea, but compares inter-quantile ranges rather than variances. He finds that factor inputs in agriculture explain virtually none of the observed international income variation in either statistic, while they explain around 60% in the manufacturing data. In further analysis he uses the same methodology to compare counterfactual cross-country income variation if all countries were assumed to enjoy the US-levels of TFP but kept their factor allocations fixed. This leads him to conclude that taking account of differences in sectoral composition actually *decreases* the share of cross-country income variation that can be explained with factor endowment, such that TFP level differences, especially those in agriculture, still account for most of the international income variation.

Restuccia (2004) develops sectoral production functions where TFP levels are allowed to differ across sectors and countries, while all countries are subject to be the same sector-specific exogenous TFP growth rates. His model assumes the production of a single homogeneous good using a traditional or modern technology and requires that marginal factor products equalize across sectors. Calibrating this model to the US growth experience his simulations investigate the impact of barriers to capital accumulation on cross-country income differences and aggregate TFP levels. He finds that TFP level differences required to account for a given income disparity are reduced by 50%, compared to a standard aggregate growth model without barriers to capital accumulation. In the face of these barriers, capital accumulation is reduced and factor allocation across sectors is distorted, resulting in reduced aggregate output and accounting for the aggregate TFP differences across countries.[11]

A focus on agriculture in its contribution to aggregate growth leads Restuccia et al. (2008) to a simplified dual economy model without capital (but intermediate inputs and land in agriculture), where the ratio of TFP levels between sectors is assumed constant across countries. They do however assume wage dualism, translating into lower wages in agriculture. The authors calibrate their model to the US growth experience, and assess what proportion (results in parenthesis) of observed agricultural employment share (75%), agricultural input-output ratio (95%), agricultural (18%) and aggregate (27%) labour productivity can be explained by cross-country differences in TFP levels, barriers to intermediate input use and per capita land

[10] The model further assumes that all human capital is employed in manufacturing.

[11] The validity of the barriers to capital accumulation model in Restuccia (2004) has however been questioned by Landon-Lane and Robertson (2007), who comment that the barriers effect in a two-sector model is necessarily identical to the effect in an aggregate model.

in their model. They conclude that differences in TFP levels required to match observed aggregate output are smaller once the role of the agricultural sector in development is accounted for, but acknowledge the poor predictions of their model for labour productivity.

Gollin et al. (2002) present a dual economy model where the agricultural sector is distinguished by three different production technologies: a traditional technology with labour and land; an intermediate technology as the former but influenced by policy and technology (TFP levels & growth); and a modern technology which in addition uses capital as factor input. Manufacturing is described as in our encompassing model above. TFP levels are modelled to differ across sectors and countries, while sector-specific exogenous TFP growth is assumed identical across countries. The authors then carry out stylized numerical experiments for their calibrated model,[12] investigating the impact of different sectoral TFP levels on overall growth outcomes and structural transformation. Given their model setup this confirms the importance of agricultural TFP levels for initiating industrialization, contrasted with the significance of manufacturing TFP for the pace of 'catch-up'.

Models discussed in this sub-section commonly use simplified dual economy models or focus on very specific details of the production process. All studies reviewed rely on some form of calibrated accounting exercises or simulation to study the extent of or the reduction of the importance of TFP levels for aggregate growth in their model. These methods in general are highly stylized and assume marginal capital product equalization.

2.2.3 Productivity differences between sectors: marginal factor product dualism

A large number of theoretical studies explore the dual economy model assuming marginal product *equality* across sectors (e.g. Matsuyama, 1992; Echevarria, 1997; Kongsamut et al., 2001; Laitner, 2000).[13] As noted above, in the presence of wage and/or rental rate dualism the equilibrium output will be lower than in the undistorted first-best equilibrium. Resolution of the factor price dualism allows for movement toward the first-best equilibrium with positive effects for aggregate output (Temple, 2005), while the presence of a persistent marginal productivity gap between sectors may explain the importance of structural change for economic development (Robinson, 1971; Vollrath, 2009b). The following studies integrate sectoral marginal product differences for labour (MPL), and in some cases also for capital (MPK), in an open dual economy model. Empirical analysis is by cross-country regression (Robinson, 1971; Dowrick and Gemmell, 1991; Temple and Wößmann, 2006) and/or accounting exercise (Temple, 2004; Vollrath, 2009b).

[12] They calibrate the model to the UK's development path over the past 250 years as benchmark country. The capital share in manufacturing is set to .5, while the capital share in modern agriculture is set to .1 (labour coefficient .6 in modern agriculture and .7 in the two backward technologies).

[13] Note that all of these model a closed economy — with the exception of Matsuyama (1992) who models both a closed and open economy. Robertson (1999) considers wage dualism in an extension to his closed economy model.

Robinson (1971) extends a cross-country growth regression model to account for structural change. His dual economy setup allows for sectoral marginal factor product dualism but abstracts from technical progress and land in the production functions. Apart from terms for labour growth and investment ratio his regression model includes two terms measuring the growth contribution of factor transfers between sectors with differential marginal factor products.[14] When estimated using pooled OLS for a short panel of LDC observations the structural change term for labour is significant, while that for capital is found only marginally significant.

The model by Vollrath (2009b) adopts sectoral production functions similar to our own encompassing model, explicitly accounting for land, allowing for marginal factor product dualism and for TFP levels to differ across sectors. In addition he integrates sectoral human capital derived from Timmer (2002), capital stock data for agriculture and manufacturing is taken from the Crego et al. (1998) dataset. He imposes differential capital coefficients in agriculture and manufacturing (following Caselli, 2005) and then calculates MPL and MPK ratios between sectors: results suggest considerable marginal factor product dualism. Sectoral TFP levels are then backed out from the respective production functions. Results from the development accounting exercise suggest that the substantial factor market inefficiencies identified are instrumental in explaining aggregate income variation across countries, and that sectoral TFP-levels "appear to have almost no impact on the relative incomes of rich and poor countries" (Vollrath, 2009b, p.29).[15] Further analysis suggests that developing countries with significant factor market distortions even tend to have higher levels of manufacturing TFP than developed countries with competitive markets. The implication that factor inputs drive output are in direct contrast to Caselli (2005), but Vollrath (2009b) proposes that the latter's results derive from his treatment of physical and human capital data.

The model by Dowrick and Gemmell (1991) allows for marginal labour product differentials and differences in TFP growth rates across sectors and countries.[16] Marginal capital product equalization across sectors is assumed, based on earlier work by the authors. Sectoral TFP growth is specified as a linear function of exogenous sectoral TFP growth, relative sectoral labour productivity (against a benchmark country), and for agricultural TFP growth further the labour productivity ratio of agriculture over industry (country-specific).[17] They estimate this model (with capital and labour as factor inputs) for two period-averaged cross-sections of rich and middle-income countries, and separately for a single averaged cross-section of a

[14] This setup assumes identical marginal factor product differential between sectors across all countries.

[15] Development accounting analysis by Córdoba and Ripoll (2009) similarly concludes that the source of the sectoral wage gap determines the contribution of TFP variation to cross-country income per worker. The importance of TFP is reduced if particularly low human capital in agriculture, home production or rural-urban living cost differentials are assumed, whereas it increases if high human capital in manufacturing is taken as the source of the wage gap.

[16] They use the ratio of average factor productivities in the two sectors as proxy for the marginal differentials.

[17] Their empirical model is thus an extension of Feder (1986) allowing for more flexibility in the MP differences and containing additional terms deriving from their TFP growth specification.

more diverse set of countries, allowing for structural breaks by level of development. For the former dataset, they conclude that the degree of labour market disequilibrium is proportional to the level of development. Further, they identify substantial differences in TFP growth across sectors, pointing to TFP level convergence in manufacturing and a mixture of convergence and divergence at difference stages in agriculture. For the latter dataset, they find that industrial TFP growth in the poorest countries is far below that of rich and middle-income countries, leaving the former's technology levels to fall further and further behind. In agriculture they identify technology 'catch-up' for the poorest countries, confirming the differential TFP growth rates in this expanded sample.[18] Poor countries have fallen further behind rich and middle-income countries in aggregate growth terms due to the small contribution of their agricultural sector to aggregate GDP (only about 30%).

Research conducted by Jon Temple investigates the relationship between wage dualism and cross-country TFP growth differences using calibrated models as well as regression analysis. Temple (2004) develops a model which I have taken as foundation for the encompassing framework described above, but abstracts from land in agriculture and does not consider marginal capital product dualism. Due to his specification and assumptions, output gains from eradicating wage dualism translate one-to-one into TFP level gains. His calibration exercise for Sub-Saharan Africa, East Asia and Latin America uses technology parameters derived from the data[19] and assumes a manufacturing wage premium of 40%. The purpose of the exercise is to assess how a reallocation of labour between sectors (equivalent to the elimination of wage dualism and urban unemployment) will influence aggregate output in a typical country within each region. Temple finds relatively modest aggregate output improvement following the elimination of these labour market distortions. Sectoral composition of employment and output however changes significantly. Thus while tying labour market distortion closely to potential failure to industrialize, this study finds only modest effects on aggregate output growth upon eradication of wage dualism.

Temple and Wößmann (2006) also analyze the impact of wage differentials on aggregate output growth. They derive an empirical model where terms for wage differential and speed of adjustment in disequilibrium are additional regressors to sectoral TFP growth terms. This empirical specification allows them to test for their hypothesis that the growth bonus of structural change increases with the extent of wage dualism. They do not account for the possibility of sectoral MPK differences and abstract from land as factor input. Their empirical analysis comprises a TFP accounting exercise using calculated TFP growth rates from existing studies, and period-averaged growth regressions à la Mankiw et al. (1992) extended by the two

[18] Note that their estimation results also suggest differential marginal capital products between the group of rich & middle-income countries and the poor countries.

[19] Based on a CRS Cobb-Douglas production function and free factor mobility the labour elasticity is derived as a function of aggregate labour share in output, and employment and output shares in agriculture, to yield labour coefficients for Sub-Saharan Africa (.8 in agriculture, .2 in manufacturing), East Asia (.93, .27) and Latin America (.83, .36).

structural change terms. The former concludes that structural change in their specification can explain a significant share of cross-country variation in aggregate TFP growth rates. Their regressions have higher explanatory power than the Mankiw et al. (1992) specification on which they are based and yield jointly significant structural change terms, thus providing some evidence for convexity of the structural change-growth relationship.

The above studies attempt to quantify the impact of factor price dualism on aggregate output or TFP growth. The early work by Robinson (1971) and Feder (1986) incorporates variables for marginal product differentials in growth regressions to estimate the contribution of structural change. This however assumes identical differentials across the sample of countries. Further, these studies abstract from disembodied technology, while their growth regression frameworks make no attempts at exploiting the panel dimension of the data. While the theoretical model in Vollrath (2009b) is sufficiently general, he does not consider estimating production functions, as his main focus is to query the methodology leading Caselli (2005) to conclude that TFP-level differences are of fundamental importance for cross-country income variation. Like in the stylized calibration exercise by Temple (2004), development accounting and TFP growth accounting force the data into a rigid mould rather than allowing it to reveal statistical significance in a well-specified estimation-based framework (Eberhardt and Teal, 2020).

In conclusion, marginal factor product differentials may play an important role in explaining barriers to structural transformation, and cross-country variation in economic performance. Significant differences in marginal capital product across sectors and a systematic link of these differences to level of development would suggest a growth engine that explains the importance of structural transformation for development.

3 An Empirical Model of A Dual Economy

In order to analyse the processes of growth at the macro-level, empirical work has primarily focused on an aggregate production estimation (see surveys in Temple, 1999; Aghion and Durlauf, 2005). While duality has featured prominently in theoretical developments there has been only limited matching of this theory to empirical models. This disjunction between theory and testing has reflected in large part the availability of data. My analysis builds on the sectoral production function models and implementation in a companion paper (Eberhardt and Teal, 2013) and I therefore sketch the econometric approach only briefly in the following sections.

3.1 Empirical specification

The analysis of growth and development using cross-country data is still dominated by variants on the 'convergence equation' introduced by Mankiw et al. (1992), where variables are averaged over the entire time-horizon and estimation is carried out in a single cross-country regression (Durlauf et al., 2005). The multiple shortcomings of this approach have been discussed in great detail in Eberhardt and Teal (2011). The latter also point to a number of modeling concerns I will address in the empirical analysis, namely parameter heterogeneity, cross-section dependence and variable time-series properties. Briefly, the notion that equilibrium relationships may differ fundamentally across countries (perhaps at different stages of development) is a familiar one, both in the theoretical (Murphy et al., 1989; Azariadis and Drazen, 1990; Durlauf, 1993; Banerjee and Newman, 1993) and empirical literatures (Durlauf et al., 2001; Kourtellos et al., 2008; Eberhardt et al., 2013; Eberhardt and Presbitero, 2015) on cross-country growth. In contrast, the notion of cross-section correlation, hypothesized to arise from common global shocks and/or local spillover effects, and concerns about variable non-stationarity have received little attention in the mainstream growth empirics literature. This is despite the rapid developments in econometric theory over the past two decades (Bai and Ng, 2004; Andrews, 2005; Pesaran, 2006; Bai, 2009; Chudik and Pesaran, 2015). In the context of cross-country growth and development analysis, the potential for cross-section correlation is particularly salient, given the interconnectedness of countries through history, geography and trade relations. Besides a number of spatial econometric approaches, where the nature of the spatial association is imposed by the econometrician (Conley and Ligon, 2002; Ertur and Koch, 2007) and which capture only interdependence of a local nature (Chudik et al., 2011; Pesaran and Tosetti, 2011), only a limited number of applied papers have concerned themselves with these matters (Eberhardt et al., 2013; Eberhardt and Teal, 2013, 2020).

The empirical setup follows the general model laid out in Eberhardt and Teal (2011), adopting a common factor representation for a standard log-linearized Cobb-Douglas production function model. Each sector is modelled separately — I do not identify this multiplicity in our general model for ease of notation. Thus for $i = 1, \dots, N$, $t = 1, \dots, T$ and $m = 1, \dots, k$ let

$$y_{it} = \boldsymbol{\beta}_i' \boldsymbol{x}_{it} + u_{it} \qquad u_{it} = \alpha_i + \boldsymbol{\lambda}_i' \boldsymbol{f}_t + \varepsilon_{it} \tag{13}$$

$$x_{mit} = \pi_{mi} + \boldsymbol{\delta}_{mi}' \boldsymbol{g}_{mt} + \rho_{1mi} f_{1mt} + \ldots + \rho_{nmi} f_{nmt} + v_{mit} \tag{14}$$

$$\boldsymbol{f}_t = \boldsymbol{\varrho}' \boldsymbol{f}_{t-1} + \boldsymbol{\omega}_t \qquad \text{and} \qquad \boldsymbol{g}_t = \boldsymbol{\kappa}' \boldsymbol{g}_{t-1} + \boldsymbol{\epsilon}_t \tag{15}$$

where $\boldsymbol{f}_{\cdot mt} \subset \boldsymbol{f}_t$ and the error terms ε_{it}, v_{mit}, $\boldsymbol{\omega}_t$ and $\boldsymbol{\epsilon}_t$ are white noise. Equation (13) represents the production function model, with y as sectoral value-added and $\boldsymbol{x}$ as a set of inputs: labour, physical capital stock, and a measure for natural capital stock (arable land and permanent crops) in the agriculture specification (all variables are in logs). The output elasticities for each input ($\boldsymbol{\beta}_i$) can differ across countries. To model unobserved TFP I use a combination of country-specific TFP levels (α_i) and a set of common factors ($\boldsymbol{f}_t$) with country-specific parameters $\boldsymbol{\lambda}_i$. Equation (15) specifies a flexible structure for the unobserved common factors, which are simple AR(1) processes, and includes the possibility of a unit root process ($\boldsymbol{\varrho} = 1$, $\boldsymbol{\kappa} = 1$) leading to nonstationary variables. Hence the potential of spurious regression arises if the empirical equation is misspecified. Equation (14) details the the set of $m = 1, \ldots, k$ regressors; some of the common factors contained in the covariates are also assumed to be driving the unobservables in the production function equation (u_{it}). This setup leads to endogeneous regressors, hence making it difficult to identify $\boldsymbol{\beta}_i$ separately from $\boldsymbol{\lambda}_i$ and $\boldsymbol{\rho}_i$ (Kapetanios et al., 2011).

3.2 Identification

Our empirical approach in Eberhardt and Teal (2013) emphasized the importance of parameter and factor loading heterogeneity across countries: we developed how the Common Correlated Effects (CCE) estimators introduced in Pesaran (2006) and extended to nonstationary variables in Kapetanios et al. (2011) are able to identify the production technology parameters $\boldsymbol{\beta}_i$ by adding cross-section averages of all variables in the empirical model to the regression equation, and allowing these averages to have heterogeneous parameters across countries. The preferred heterogeneous CCEMG estimator thus represents an extension to a standard country regression model (Pesaran and Smith, 1995) and was shown to perform well even when the cross-section dimension N is small, when variables are nonstationary, subject to structural breaks and in the presence of heteroscedastic or spatially correlated errors (Pesaran, 2006; Kapetanios et al., 2011; Bond and Eberhardt, 2013). The estimator identifies $\boldsymbol{\beta}_i$ or its cross-country average by accounting for the presence of the unobserved factors in equation (13), such that an OLS regression no longer obtains residuals that are correlated with the observed inputs.

3.3 Data description

Descriptive statistics and a more detailed discussion of the data can be found in the Appendix. Briefly, I conduct empirical analysis for the agricultural sector, using the sectoral investment series of Crego et al. (1998) and output from the World Development Indicators (WDI, World Bank, 2008), in addition to sectoral labour and land data and FAO (2007); and for the manufacturing sector, using the Crego et al. (1998) sectoral investment series, output data from the WDI and labour data from UNIDO (2004). I construct the capital stocks in agriculture and manufacturing from the investment data using the perpetual inventory method (see Klenow and Rodriguez-Clare, 1997b, for details). Direct comparison across sectors is possible given the underlying Crego et al. (1998) sectoral investment data for agriculture and manufacturing. Following the suggestions in Martin and Mitra (2002) all monetary values are transformed into US$ 1990 values (in the case of the capital stocks the transformation is applied to the investment series): my open economy model emphasizes *tradable* goods production.

I end up with an unbalanced panel of 40 developing and developed countries over the 1963 to 1992 period (918 observations, average $T = 23$) — the sample makeup is detailed in Table

A-I, descriptive statistics are provided in Table A-II (see Data Appendix). Approximately half of the sample countries are present-day 'industrialized economies', only eight are in Africa. However, these numbers are somewhat deceiving since structural change and development in many of today's industrialized economies has primarily been achieved during our period of study: e.g. the share of agricultural value-added in GDP for Ireland, South Korea, Finland, and Portugal is between two and four times larger in 1963 than at the sample end in 1992.[20]

4 Production Function Results

Table 1 reports the preferred CCEP and CMG estimates from the production function regressions, reporting pooled and heterogeneous parameter models for agriculture and manufacturing respectively. These preferred models emerge from a range of diagnostic tests which confirm that residuals are stationary and cross-sectionally independent.

Table 1: Production Function Results

Technology	*Homogeneous*						*Heterogeneous*	
Sector	Agriculture			Manufacturing			Agri	Manu
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Estimator	**2FE**	**CCEP**$^\flat$	**IFE**	**2FE**	**CCEP**$^\flat$	**IFE**	**CMG**$^\flat$	**CMG**$^\flat$
log capital pw	0.663	0.526	0.502	0.808	0.468	0.492	0.620	0.339
$\hat{\beta}_K$	[18.00]**	[6.25]**	[6.10]**	[22.22]**	[6.77]**	[7.21]**	[2.98]**	[4.59]**
log land pw	0.080	0.126	0.261				0.073	
$\hat{\beta}_N$	[2.36]*	[0.95]	[2.65]*				[0.38]	
Implied β_L‡	0.257	0.474	0.237	0.192	0.532	0.508	0.380	0.661
$\hat{e}$ integrated$^\natural$	I(1)	I(0)	I(0)	I(1)	I(0)	I(0)	I(0)	I(0)
CD test p-value$^\sharp$	0.00	0.52	0.03	0.00	0.92	0.26	0.73	0.24
RMSE	0.129	0.089	0.075	0.130	0.066	0.066	0.068	0.049

Notes: *, ** indicate significance at 5% and 1% level respectively. White heteroscedasticity-robust standard errors for 2FE models, bootstrapped standard errors for CCEP models (100 replications), variance estimator following Pesaran and Smith (1995) for CMG models. $\flat$ Model includes cross-section average for *both* the agricultural and manufacturing sector variables respectively. $\ddagger$ Based on significant parameter estimates. $\natural$ Order of integration of regression residuals, determined using Pesaran (2007) CIPS (full results available on request). $\sharp$ Pesaran (2015) CD-test, H_0: cross-sectionally independent residuals. RMSE reports the root mean squared errors.

The models implemented in Eberhardt and Teal (2013) represent a variant on the standard CCE estimators, where we exploited information from both the panel data from the own sector as well as the other industrial sector, in the spirit of Pesaran et al. (2013). This implies that our empirical approach also allows shocks to the agricultural sector, e.g. commodity price shocks (see Eberhardt and Presbitero, 2021), to affect production and factor accumulation in the

[20]The Technical Appendix contains results for stationarity and cross-section dependence test covering the variables entering the regression equations, namely output, capital, land (all in logs of per worker terms) and labour (in logs), suggesting all level series are I(1) and highly cross-sectionally dependent.

manufacturing sector and vice versa. This empirical specification is intuitive and was found to be an improvement on the model which only includes own-sector cross-section averages. For comparative purposes I also provide the estimates for two-way fixed effects models in [1] and [4] of Table 1, which represent the pooled model of choice in a number of existing empirical studies, as well as the interactive fixed effects estimator (Bai, 2009, IFE) which assumes common technology parameters but similarly to the CCE builds on a multi-factor error structure. While in the case of agriculture the estimates for 2FE, CCEP and CMG are not substantially different, it is notable that the 2FE residuals are both nonstationary and cross-sectionally dependent, thus indicating serious empirical misspecification. The same problem arises for the manufacturing 2FE model, where the capital coefficient is substantially inflated. The IFE estimation for agriculture is found to insufficiently address cross-section dependence, which throws these results into question.

5 Duality and the Determinants of Growth

In this section I return to the themes developed in Section 2 and ask how the dual economy model can contribute to our understanding of the sources of economic growth. I investigate in turns TFP growth rates, TFP levels and marginal factor product dualism.

5.1 TFP growth differences as a potential source of aggregate growth

Technical progress in form of TFP growth in aggregate growth accounting exercises has frequently been hailed as the dominant source of growth in empirical studies (Easterly and Levine, 2001; Klenow and Rodriguez-Clare, 1997a), a notion which as our discussion in Section 2 suggests extends to the analysis of sectoral data. Since Cobb-Douglas production estimations and growth accounting are essentially identical approaches (Chen, 1997) the unobserved common factors in our regression-based model can capture the sectoral TFP growth values (Durlauf et al., 2005; Bond et al., 2010).

Table TA-III in a Technical Appendix provides country-level TFP growth estimates — in this and the following analysis I present results for the CCEP and CMG estimators in the preferred specifications (see Table 1), where in the agriculture equations I always include land per worker. For comparison with the empirical results in Martin and Mitra (2002, henceforth M&M) I also present results for their specification as well as for a 2FE estimator — both models assume country-sector specific TFP but the latter assumes common sectoral TFP evolution while the former allows for heterogeneous but linear sectoral TFP growth across countries. For the 2FE and CCE models TFP growth is constructed from the data in two steps: first I impose the estimated output elasticities with respect to observable inputs on the data, accounting for the white noise error component, thus

$$\hat{\text{TFP}}_{it} = y_{it} - \hat{\boldsymbol{\beta}}_i' \boldsymbol{X}_{it} - \hat{e}_{it} \tag{16}$$

where $\hat{\boldsymbol{\beta}}_i$ are the technology parameter estimates (homogeneous for 2FE and CCEP), $\boldsymbol{X}_{it}$ represents the factor inputs and $\hat{e}_{it}$ is the 2FE, CCEP or CMG regression residual. In a second step I simply compute annual TFP growth as the first difference of this TFP series.[21]

I find that the average sector-specific TFP growth rate for the entire sample differs considerably between the estimates following M&M on one hand and the 2FE, CMG and CCEP estimates on the other — see Table 2 and Table TA-III in the Technical Appendix. In agriculture the M&M growth rate of around 1.2 percent per annum is roughly doubled in the two CCE estimates, whereas in manufacturing the mean estimate for the CCEP and CMG estimators are around four times that of M&M, which yields less than 0.8 percent per annum. Sample average TFP growth in agriculture exceeds that in manufacturing in the M&M case whereas the reverse is observed for all other models — note that differences between these means are not statistically significant. Consistently across all models in about half of all countries the average TFP growth rate in agriculture exceeds that in manufacturing.

Average TFP growth estimates on their own are not necessarily all that meaningful for an analysis of growth determinants. In Table 3 I provide a decomposition analysis to highlight the respective contribution of factor input growth and TFP growth on output. For Panel (A) the weighted TFP and factor input growth terms are divided by the country-specific *aggregated* VA growth per worker, the sum of sectoral growth where the weights represent the share of sectoral VA in aggregated VA. This statistic is calculated for each country over the entire time horizon and the figures presented in the table represent descriptive statistics for all countries: mean, median and standard deviation ('unweighted') as well as the robust means, t-ratios and 99% confidence intervals.

Comparing results for the 2FE, CCEP and CMG all indicate the importance of factor input growth: 50 to 80 percent of the variation in aggregated VA growth per worker is explained by factor inputs, whereas the contribution of TFP growth is comparatively modest — the benchmark in this analysis is the work reviewed in Caselli (2005) suggesting that 'it's not factor accumulation' (Easterly and Levine, 2001). The same analysis focused on the sector-level (share of TFP and factor input growth in sectoral VA per worker growth) indicates that this result is not due to our stylized aggregation.

[21] In practice I do not rely on annual estimates for TFP growth but construct average growth rate using the first and last observed TFP-level estimates. Note further that the problems related to the correct computation of TFP-levels need not concern us for TFP growth estimates, since these are unaffected by the issues about heterogeneity faced in the TFP level estimation case.

Table 2: Computed TFP-growth rates (average %age rate per annum)

		Panel A: Agriculture							
wbcode	country	[1] M&M		[2] 2FE		[3] CCEP		[4] CMG	
MLT	Malta	3.49	△	7.03	△	7.58	△	7.57	△
GRC	Greece	2.85		4.52	△	6.13	△	6.31	△
CYP	Cyprus	-1.83	▼	5.29	△	5.93	△	5.86	△
PRT	Portugal	-0.34		4.24		5.79	△	5.70	△
IRL	Ireland	1.04		4.28		5.32	△	5.64	△
NZL	New Zealand	0.39		0.07	▼	-0.04	▼	0.05	▼
ITA	Italy	3.25	△	1.20		-0.32	▼	-0.25	▼
USA	United States	0.32		0.45		-0.84	▼	-0.65	▼
AUS	Australia	1.96		0.29	▼	0.07	▼	-1.01	▼
MDG	Madagascar	-0.50	▼	-0.09	▼	-0.95	▼	-1.07	▼
Sample	Max	3.49		7.03		7.58		7.57	
	Robust mean	1.18		2.19		2.31		2.32	
	[t-statistic]	[4.66]**		[8.57]**		[6.92]**		[6.79]**	
	Min	-1.83		-0.09		-0.95		-1.07	

		Panel B: Manufacturing							
wbcode	country	[1] M&M		[2] 2FE		[3] CCEP		[4] CMG	
MWI	Malawi	1.39		8.25	△	8.52	△	8.54	△
MLT	Malta	5.25	△	4.85	△	7.55	△	7.43	△
KOR	South Korea	2.58	△	6.83	△	6.41	△	6.37	△
IRL	Ireland	2.52		3.40		5.98	△	5.78	△
CHL	Chile	2.28		5.10	△	5.56	△	5.55	△
USA	United States	-0.88		0.02	▼	1.05		0.99	
PHL	Philippines	-0.75		1.70		0.51	▼	0.50	▼
CYP	Cyprus	-1.52	▼	0.84		0.27	▼	0.25	▼
LKA	Sri Lanka	-1.85	▼	0.95		-0.17	▼	0.05	▼
MUS	Mauritius	-2.43	▼	0.04		-0.78	▼	-0.66	▼
MDG	Madagascar	-2.74	▼	-2.38	▼	-2.76	▼	-2.76	▼
Sample	Max	5.25		8.25		8.52		8.54	
	Robust mean	0.77		2.23		2.44		2.44	
	[t-statistic]	[3.00]**		[7.59]**		[6.76]**		[6.83]**	
	Min	-2.74		-2.38		-2.76		-2.76	

		Panel C: Agriculture > Manufacturing			
		[1] M&M	[2] 2FE	[3] CCEP	[4] CMG
Sample	count	21	24	23	23

Notes: Sample of $N = 40$ countries. For each empirical model I indicate the five countries with the highest TFP growth rates with △ and the five countries with the lowest TFP growth rates with ▼. These results are in order of the CMG estimates in column [4] of each panel. I add the US estimates in manufacturing for comparison. M&M reports results using the specification in Martin and Mitra (2002), who adopt a country fixed effect model with country-specific linear trends, such that TFP evolution is country-sector specific but confined to linearity.

Table 3: Growth decomposition

		Unweighted			Robust Statistics		
Panel (A): Aggregated growth†							
		mean	median	st.dev	mean	t-statistic	99% CI
2FE	TFP growth	0.13	0.09	0.16	0.11	[4.64]**	0.048 — 0.181
	Factor input growth	0.83	0.71	0.44	0.79	[12.64]**	0.623 — 0.962
CCEP	TFP growth	0.24	0.27	0.55	0.31	[7.28]**	0.198 — 0.432
	Factor input growth	0.51	0.46	0.27	0.49	[12.93]**	0.384 — 0.587
CMG	TFP growth	0.15	0.27	0.70	0.22	[3.51]**	0.050 — 0.384
	Factor input growth	0.63	0.56	0.84	0.56	[7.59]**	0.362 — 0.763
Panel (B): Growth in Agriculture							
		mean	median	st.dev	mean	t-statistic	99% CI
2FE	TFP growth	-0.16	0.17	1.55	0.22	[5.25]**	0.106 — 0.331
	Factor input growth	0.54	0.69	0.77	0.72	[28.27]**	0.652 — 0.790
CCEP	TFP growth	0.65	0.43	1.61	0.43	[8.32]**	0.287 — 0.564
	Factor input growth	0.33	0.51	0.76	0.53	[19.36]**	0.455 — 0.603
CMG	TFP growth	-0.21	0.28	3.96	0.30	[3.98]**	0.096 — 0.506
	Factor input growth	1.10	0.62	3.48	0.64	[6.74]**	0.383 — 0.897
Panel (C): Growth in Manufacturing							
		mean	median	st.dev	mean	t-statistic	99% CI
2FE	TFP growth	0.24	0.07	1.01	0.07	[3.50]**	0.016 — 0.122
	Factor input growth	1.31	1.03	2.58	0.98	[14.09]**	0.789 — 1.163
CCEP	TFP growth	-1.53	0.34	11.49	0.38	[6.49]**	0.224 — 0.543
	Factor input growth	0.77	0.61	1.52	0.58	[14.09]**	0.465 — 0.686
CMG	TFP growth	-0.95	0.25	5.52	0.24	[2.60]*	-0.010 — 0.494
	Factor input growth	1.25	0.60	3.21	0.59	[6.01]**	0.322 — 0.848
Panel (D): Aggregated growth neglecting sector structure							
		mean	median	st.dev	mean	t-statistic	99% CI
2FE	TFP growth	0.13	0.09	0.14	0.11	[5.58]**	0.056 — 0.163
	Factor input growth	1.04	0.96	0.44	0.92	[19.14]**	0.790 — 1.050
CCEP	TFP growth	0.12	0.27	0.45	0.20	[3.51]**	0.045 — 0.348
	Factor input growth	0.85	0.78	0.36	0.75	[19.14]**	0.645 — 0.857
CMG	TFP growth	0.13	0.09	0.14	0.11	[5.58]**	0.056 — 0.163
	Factor input growth	0.88	0.90	1.01	0.88	[10.68]**	0.654 — 1.098

Notes: The table presents the average share of aggregate (sector) growth attributed to TFP growth and factor input growth respectively. Computations are based on the preferred agriculture and manufacturing production functions in Table 1. † I computed the weighted average share of TFP growth and factor input growth in aggregated data growth (all values are in per worker terms), where the latter is computed as the growth rate of per worker output (with output the sum of agriculture and manufacturing output and total workforce the sum of the economically engaged workers in both sectors). The weights applied represent the shares of sectoral output in aggregated output.

5.2 TFP level differences as a potential source of aggregate growth

Rather than differential technical progress, differential TFP levels between sectors have been suggested as the source of growth variation across countries (Caselli, 2005). TFP levels "capture the differences in long-run economic performance that are most directly relevant to welfare" and their analysis is therefore preferable to that of TFP growth which is deemed to capture short-term fluctuations (Hall and Jones, 1999, p.85).

From the preferred country regressions I can obtain estimates for the intercept, technology parameters, and the parameters on the cross-section averages for the CCEP and CMG specification respectively. One may be tempted to view the coefficients on the intercepts as TFP level estimates, just like in the pooled fixed effects case. However, Eberhardt and Teal (2020) develop in detail that once technology parameters in the production function are allowed to differ across countries the regression intercept can no longer be interpreted as a TFP-level estimate, since the *ceteris paribus* assumption no longer holds. Furthermore, the Pesaran (2006) approach combines other values than merely α_i in the estimates of a country-sector intercept, as is shown in Eberhardt et al. (2013, p.440). An alternative measure for TFP-levels, which is robust to parameter heterogeneity and the problem related to the interpretation of the constant term is the locus of the first capital stock observation along the trajectory of the regression line (in output-capital stock space — both in per worker terms).[22] In the 2FE specification this *adjusted* base-year TFP-level is defined as

$$\hat{a}_i + \hat{\beta} \log(\mathrm{K/L})_{0,i} \tag{17}$$

where $\log(K/L)_{0,i}$ is the country-(sector)-specific base-year value for capital per worker, $\hat{\beta}$ represents the (sector-specific) capital coefficient and $\hat{a}_i$ is the coefficient for the intercept.

For the CCE estimators I need to change this approach to extracting the unobserved common factors (multiplied by the heterogeneous factor loadings) using the technology parameter estimates $\hat{\beta}_i$ ($\hat{\beta}$ for CCEP) and CCE regression residuals $\hat{e}_{it}$

$$y_{it} - \hat{\beta}_i \log(\mathrm{K/L})_{0,i} - \hat{e}_{it} \tag{18}$$

In the results I will contrast the adjusted TFP level estimates derived from this approach with a standard practice in the literature, where the TFP level differences are captured by the fixed effects: these represent the relative TFP level of each country compared with that of the omitted benchmark country.[23] As I work with an equation in logs each country's relative TFP

[22] In the agriculture sector this computation is adjusted to take the impact of land per worker into account. I present the manufacturing case for simplicity.

[23] If I use the empirically equivalent Least Squares Dummy Variable (LSDV) estimator, I am able to select the benchmark country to be omitted (here: the United States) and can read off the country-specific relative TFP-level from the country dummy coefficients $\hat{\eta}_{ij}$.

level is obtained from the country dummy as

$$\left(\frac{\text{TFP}_i}{\text{TFP}_{US}}\right)_j = \exp(\hat{\eta}_{ij}) \tag{19}$$

since the implicit coefficient on the omitted benchmark country is zero. Table 4 presents the outcome of this exercise each country's TFP level is expressed with reference to that of the US under the 2FE (LSDV) entry. Figure 1 plots the relative TFP level estimates for all countries where those economies are highlighted for which there are considerable differences in the sectoral TFP level estimates.

Table 4: Relative TFP-level estimates (USA$=1$)

Model	mean	median	st.dev.	min	max
Panel (A): Agriculture					
2FE (LSDV)†	1.17	1.01	0.59	0.41	2.79
2FE	0.77	0.78	0.17	0.37	1.00
CCEP	0.77	0.77	0.17	0.38	1.00
CMG	0.78	0.78	0.17	0.38	1.00
Panel (B): Manufacturing					
2FE (LSDV)†	0.54	0.55	0.20	0.17	1.00
2FE	0.87	0.87	0.10	0.61	1.01
CCEP	0.86	0.87	0.10	0.61	1.03
CMG	0.86	0.87	0.10	0.61	1.03

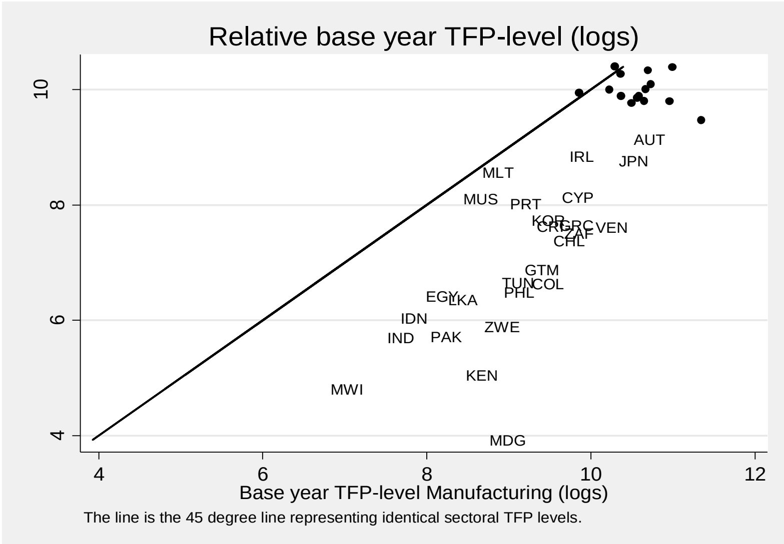
Notes: † Transformed coefficients on the country dummies (see main text) from a standard LSDV regression with $T-1$ year dummies. All other results adopt the adjustment procedure for TFP level computation described in the main text before computing relative values (with reference to US TFP level).

As can be seen the conventional 2FE (LSDV) approach leads to a vast range of TFP levels in agriculture, from 41% to 279% of the US-level. In comparison the adjusted TFP levels for 2FE, CCEP and CMG all yield a range between around 40% and 100% (thus the US has highest agricultural TFP level). In the manufacturing data the conventional fixed effects approach yields a range of 17% to 100%, whereas the adjusted versions vary between 60% and 100%. As a result the variance of TFP levels in the adjusted approach is between *half* and *less than one third* of that in the conventional approaches.

The top-5 countries in terms of adjusted agricultural and manufacturing TFP-levels (CMG model) are Australia, the US, the Netherlands, the UK and Sweden, and Iran, the US, Italy, Sweden and the Netherlands respectively. Bottom of the list are Pakistan, India, Kenya, Malawi and Madagascar in Agriculture and Pakistan, Egypt, Indonesia, India and Malawi in Manufacturing — all of these estimates refer to the base-year, which varies in the data but for these countries is in the 1960s.

Comparing the country-specific relative TFP levels across sectors (not reported) I can reject the

Figure 1: Relative Adjusted TFP levels for Agriculture and Manufacturing



Notes: Agricultural TFP level on the y-axis, Manufacturing TFP level on x-axis. Both sets of TFP estimates are for the CMG models and adjusted using the methodology described in the main text.

modeling assumption by Restuccia et al. (2008) that the sectoral TFP-ratio is *constant* across countries. The mean TFP ratio (agriculture/manufacturing) is 89% of the U.S. benchmark ratio (st. dev. 13%, min 47%, max 107% — all values are for the CMG results). Thus TFP level differences *between sectors* vary greatly across my sample, with proportionally more variation deriving from the agricultural sector.

In this subsection I considered TFP level differences between sectors as the source of aggregate growth. It bears reminding that in contrast to previous quantitative studies (Restuccia, 2004; Caselli, 2005; Vollrath, 2009b) I carried out estimation of TFP levels, rather than deriving results from calibration exercises. My findings reject the assumption of identical TFP levels across sectors as well as an alternative suggestion of identical TFP level differences between sectors across countries. I also cannot confirm the presence of substantial TFP level differences within both the agricultural and manufacturing sectors. Somewhat tellingly, Australia and New Zealand (practitioners of industrial agriculture) represent the only countries where agricultural TFP levels in the early 1960s were higher than in manufacturing.

5.3 Sectoral productivity differences: wage/rental rate dualism

Following the estimation of sectoral production functions and the analysis of TFP differences across countries I now compute marginal labour products (MPL) and marginal capital products (MPK) from the estimates obtained. For a CRS Cobb-Douglas production function sectoral MPL and MPK are derived as (for $i = 1, \ldots, N$ and $j = a, m$)

$$Y_{ij} = A_{ij} K_{ij}^{\alpha_{ij}} L_{ij}^{1-\alpha_{ij}} \tag{20}$$

$$MPL_{ij} = (1-\alpha_{ij})A_{ij}K_{ij}^{\alpha_{ij}}L_{ij}^{-\alpha_{ij}} = (1-\alpha_{ij})A_{ij}(K/L)_{ij}^{\alpha_{ij}} \quad (21)$$
$$MPK_{ij} = \alpha_{ij}A_{ij}K_{ij}^{\alpha_{ij}-1}L_{ij}^{1-\alpha_{ij}} = \alpha_{ij}A_{ij}(K/L)_{ij}^{\alpha_{ij}-1} \quad (22)$$

where I dropped the time subscript and the $\hat{}$ signifying estimated parameters for ease of notation. However, due to the application of adjusted TFP-levels the following production function equation is adopted for the computations

$$Y_{ij} = A_{ij}^{\star}K_{ij}^{\alpha_{ij}}L_{ij}^{1-\alpha_{ij}} = e^{\left\{\log(\mathrm{Y/L})_{ij}-\alpha_{ij}\log(\mathrm{K/L})_{0,ij}-e_{it}\right\}}K_{ij}^{\alpha_{ij}}L_{ij}^{1-\alpha_{ij}} \quad (23)$$

which leads to alternative MPL and MPK equations. For the former

$$MPL_{ij} = (\partial Y_{ij}/\partial L_{ij}) = (1-\alpha_{ij})A_{ij}^{\star}K_{ij}^{\alpha_{ij}}L_{ij}^{-\alpha_{ij}} + \left(\partial A_{ij}^{\star}/\partial L_{ij}\right)K_{ij}^{\alpha_{ij}}L_{ij}^{1-\alpha_{ij}} \quad (24)$$
$$= (1-\alpha_{ij})A_{ij}^{\star}(K/L)_{ij}^{\alpha_{ij}} + [\alpha_{ij}(1/\mathrm{L_{0,ij}}) - (1/\mathrm{L_{ij}})]\,A_{ij}^{\star}K_{ij}^{\alpha_{ij}}L_{ij}^{1-\alpha_{ij}} \quad (25)$$
$$MPL_{0,ij} = (1-\alpha_{ij})A_{0,ij}^{\star}(K/L)_{0,ij}^{\alpha_{ij}} - (1-\alpha_{ij})A_{0,ij}^{\star}(K/L)_{0,ij}^{-\alpha_{ij}} \quad (26)$$

where equation (25) represents the general marginal labour product for sector j in country i and equation (26) refers to its value in the base year — the latter is much simplified. The first term on the RHS of (26) is a standard MPL estimate where instead of the 'conventional' TFP A I employ the adjusted TFP $A^{\star}$; the second term adjusts for the (Y/L) and (K/L) terms contained in $A^{\star}$.[24] Similarly for MPK to yield

$$MPK_{ij} = \alpha_{ij}A_{ij}^{\star}(K/L)_{ij}^{\alpha_{ij}-1} - [\alpha_{ij}(1/\mathrm{K_{0,ij}})]\,A_{ij}^{\star}K_{ij}^{\alpha_{ij}}L_{ij}^{1-\alpha_{ij}} \quad (27)$$
$$MPK_{0,ij} = \alpha_{ij}A_{0,ij}^{\star}(K/L)_{0,ij}^{\alpha_{ij}-1} - \alpha_{ij}A_{0,ij}^{\star}(K/L)_{0,ij}^{\alpha_{ij}-1} \quad (28)$$

My analysis proceeds following the common practice in the literature of providing counterfactuals for the marginal factor products by contrasting different outcomes based on assuming different variables or parameters to be constant across countries and/or sectors. The following represent the various options:

(i) differences in TFP-levels (A) across sectors and countries,
(ii) differences in factor proportions (K/L) across sectors and countries,
(iii) differences in the output elasticity with respect to capital (α) across sectors, or
(iv) differences in output elasticity with respect to capital across sectors and across countries.

[24]Following on from equation (24) we know that $(\partial/\partial x)\,e^{f(x)} = f'(x)e^{f(x)}$, which yields

$$\partial A_{ij}^{\star}/\partial L_{ij} = \frac{\partial}{\partial L_{ij}}\left(\log(\mathrm{Y/L})_{ij} - \alpha_{ij}\log(\mathrm{K/L})_{0,i} - e_{it}\right)e^{\left\{\log(\mathrm{Y/L})_{ij}-\alpha_{ij}\log(\mathrm{K/L})_{0,i}-e_{it}\right\}}$$
$$= \left[\frac{1}{(\mathrm{Y/L})_{ij}}\left(-\frac{(\mathrm{Y/L})_{ij}}{L_{ij}}\right) - \alpha_{ij}\frac{1}{(\mathrm{K/L})_{0,ij}}\left(-\frac{(\mathrm{K/L})_{0,ij}}{L_{0,ij}}\right)\right]A_{ij}^{\star} = \left[-\left(\frac{1}{L_{ij}}\right) + \alpha_{ij}\left(\frac{1}{L_{0,ij}}\right)\right]A_{ij}^{\star}$$

which we entered into equation (25).

Table 5: Marginal Factor Products — relative to U.S. values

PANEL (A): MP WITH COMMON α AND COMMON K/L RATIO

	MPL & MPK (USA = 100)						
	obs	mean	median	st.dev.	Min.	Max.	$MP_M > MP_A$
agriculture MP[†]	40	77.90	78.11	17.41	37.81	100.15	32
manufacturing MP[†]	40	86.22	86.83	10.20	61.16	103.20	

PANEL (B): MP WITH COMMON α AND DIFFERENTIAL K/L RATIO

	MPL & MPK (USA = 100)						
	obs	mean	median	st.dev.	Min.	Max.	$MP_M > MP_A$
agriculture MPL	40	38.05	9.71	43.27	0.05	133.87	37
manufacturing MPL	40	68.33	57.74	57.17	8.70	274.93	
agriculture MPK	40	173.75	149.98	83.98	83.66	367.41	1
manufacturing MPK	40	105.75	104.45	17.49	73.74	154.77	

PANEL (C): MP WITH SECTOR-SPECIFIC α_j AND DIFFERENTIAL K/L RATIO

	MPL & MPK (USA = 100)						
	obs	mean	median	st.dev.	Min.	Max.	$MP_M > MP_A$
agriculture MPL	40	41.17	16.83	41.36	0.29	121.98	37
manufacturing MPL	40	69.32	64.96	44.97	14.63	212.80	
agriculture MPK	40	447.01	253.27	477.44	76.23	2138.41	1
manufacturing MPK	40	129.47	118.94	47.92	57.07	271.04	

PANEL (D): MP WITH HETEROGENEOUS α_{ij} AND DIFFERENTIAL K/L RATIO

	MPL & MPK (USA = 100)						
	obs	mean	median	st.dev.	Min.	Max.	$MP_M > MP_A$
agriculture MPL	40	12.45	0.33	27.23	0.02	100.00	40
manufacturing MPL	40	183.40	97.15	269.40	3.19	1110.58	
agriculture MPK	40	40.64	4.53	52.81	0.01	129.33	36
manufacturing MPK	40	741.65	102.43	962.14	2.13	2486.95	

Notes: In this analysis I adopt 'adjusted' TFP level estimates computed in the way described in the main text and based on the CMG regressions with CRS imposed (Table 1, columns [7] and [8] for agriculture and manufacturing respectively). Capital coefficients applied (robust estimates) are taken from the same regression models with the exception of Panels (A) and (B), where I employ the CMG-CRS coefficient from aggregated input and output data (see Eberhardt and Teal, 2013). Panel (A) adopts the mean capital-labour ratio from the aggregated data, Panels (B)-(C)the sector-specific mean capital-labour ratios. In Panel (C) I adopt the robust means from the *sector*-specific regressions. Using country-specific estimates for the capital-coefficient is infeasible, for theoretical (unreliable) and practical (there are values < 0 and > 1) reasons.
[†] By construction these are the same for MPK and MPL since the only source of variation across countries and sectors is in the adjusted TFP levels.

In the following I compute the sectoral marginal factor products to investigate wage and rental rate dualism. Initially factor proportions (K/L) are held constant across countries and sectors (employing the U.S. mean period value in the aggregated data) to investigate what evidence there is for dualism in marginal factor products, given that countries are assumed to use the same factor proportions but differ in efficiency levels. In all cases robust means from CMG regressions (either at the sector or the aggregated data level) are used as the basis for the capital coefficient.

Panel (A) in Table 5 presents the findings for the scenario where countries are endowed with identical capital-labour ratio and only vary in their efficiency (TFP) levels — here and in all other analyses results are re-scaled with reference to US marginal factor product (USA$= 100$).[25] Results suggest that MP in agriculture exceeds that in manufacturing in 32 countries. In Panel (B) I allow for heterogeneous capital-labour ratios, which differ by country and sector — I use country-sector-specific averages over the sample period in this and the following results. The variation in relative MPL and MPK immediately shoots up in both sectors, with the standard deviations between two and four times as large as in the previous results. Panel (C) adds sector-specific capital coefficients (albeit common across countries), where I adopt the robust mean from our sector regressions. Standard deviations for MPL settle somewhat and the range of relative MPLs is reduced; however, the MPK estimates are now substantially increased in the agricultural sector. In both cases of Panel (B) and (C) the manufacturing sector has higher MPL than the agriculture sector in most countries, but for the MPK estimates this is only the case for a single country. In our final scenario in Panel (D), where in addition capital coefficients can differ across countries[26] the results for both MPK and MPL in manufacturing display the largest standard deviations and manufacturing MP next to uniformally exceeds that in agriculture. Duality is hence a very significant wedge between the agricultural and manufacturing sectors.

6 Conclusions

This paper developed a general framework for dual economy models and used unique panel data for agriculture and manufacturing to estimate sector-level and aggregated production functions. The conceptual development built on the theoretical contributions by Temple (2005) and Corden and Findlay (1975) and my overview of the literature highlighted a number of 'sources of growth' hypothesised in the dual economy literature. The empirical analysis emphasised the contribution of the recent panel time-series econometric literature, which suggests to adopt

[25]Due to the assumptions adopted in the construction of the marginal factor products, *relative* MP values are identical this case.

[26]I cannot rely on country-specific capital parameter estimates and therefore divide the sample into three groups, representing 'low', 'intermediate' and 'high' output elasticities with respect to capital, based on the magnitude of the coefficient estimates. See Table footnote for more details.

unobserved common factors to deal with the cross-sectional dependence commonly found in macro panel data. In addition the analysis allows for nonstationarity of observable and unobservable factor inputs and I emphasised the importance of parameter heterogeneity — across countries as well as across sectors.

Following production function estimation in manufacturing and agriculture I show that average TFP growth rates in manufacturing exceed those in agriculture in around half of the countries. This result is in contrast to the findings by Martin and Mitra (2002) who emphasize the supremacy of agricultural TFP growth. The growth decomposition furthermore established that TFP growth accounts for between one-fifth and one-third of aggregated output growth, whereas factor input growth assumes a much more dominant share, a finding which is in contrast to the vast majority of empirical studies using aggregate economy data. The investigation of TFP levels suggests that manufacturing TFP commonly exceeds that of agriculture, this aside TFP difference between these two sectors are found to be far from constant across countries. Finally, the analysis of marginal factor products across countries reveasthat marginal factor product duality is very substantial once we allow for heterogeneous technology across sectors *and* countries.

References

Aghion, Philippe and Durlauf, Steven (Editors) (2005). *Handbook of Economic Growth*, Vol. 1 of *Handbook of Economic Growth* (Elsevier).

Aghion, Philippe and Howitt, Peter (1992). "A Model of Growth through Creative Destruction." *Econometrica*, Vol. 60(2): 323–51.

Aghion, Phillipe and Howitt, Peter (1998). *Endogenous Growth Theory* (Cambridge, Mass.: MIT Press).

Alvarez, Jorge A (2020). "The agricultural wage gap: Evidence from Brazilian micro-data." *American Economic Journal: Macroeconomics*, Vol. 12(1): 153–73.

Alvarez-Cuadrado, Francisco and Poschke, Markus (2011). "Structural Change Out of Agriculture: Labor Push versus Labor Pull." *American Economic Journal: Macroeconomics*, Vol. 3(3): 127–58.

Andrews, Donald W. K. (2005). "Cross-Section Regression with Common Shocks." *Econometrica*, Vol. 73(5): 1551–1585.

Arellano, Manuel and Bond, Stephen R. (1991). "Some tests of specification for panel data." *Review of Economic Studies*, Vol. 58(2): 277–297.

Azariadis, Costas and Drazen, Allan (1990). "Threshold Externalities in Economic Development." *Quarterly Journal of Economics*, Vol. 105(2): 501–26.

Bai, Jushan (2009). "Panel Data Models with Interactive Fixed Effects." *Econometrica*, Vol. 77(4): 1229–1279.

Bai, Jushan and Ng, Serena (2004). "A PANIC attack on unit roots and cointegration." *Econometrica*, Vol. 72(4): 1127–1177.

Banerjee, Abhijit and Newman, Andrew (1993). "Occupational Choice and the Process of Development." *Journal of Political Economy*, Vol. 101.

Barbier, Edward B. and Rauscher, Michael (2007). "Trade and Development in a Labor Surplus Economy." *The B.E. Journal of Economic Analysis & Policy*, Vol. 7(1).

Barro, Robert J. (1991). "Economic growth in a cross-section of countries." *Quarterly Journal of Economics*, Vol. 106(2): 407–443.

Barro, Robert J and Lee, Jong Wha (2013). "A new data set of educational attainment in the world, 1950–2010." *Journal of Development Economics*, Vol. 104: 184–198.

Basu, Susanto and Weil, David N. (1998). "Appropriate Technology And Growth." *The Quarterly Journal of Economics*, Vol. 113(4): 1025–1054.

Blundell, Richard and Bond, Stephen R. (1998). "Initial conditions and moment restrictions in dynamic panel data models." *Journal of Econometrics*, Vol. 87(1): 115–143.

Bond, Stephen R. and Eberhardt, Markus (2013). "Accounting for unobserved heterogeneity in panel time series models." Unpublished mimeo, November.

Bond, Stephen R., Leblebicioglu, Asli and Schiantarelli, Fabio (2010). "Capital Accumulation and Growth: A New Look at the Empirical Evidence." *Journal of Applied Econometrics*, Vol. 15(7): 1073–1099.

Bustos, Paula, Caprettini, Bruno and Ponticelli, Jacopo (2016). "Agricultural productivity and structural transformation: Evidence from Brazil." *American Economic Review*, Vol. 106(6): 1320–65.

Bustos, Paula, Garber, Gabriel and Ponticelli, Jacopo (2020). "Capital accumulation and structural transformation." *The Quarterly Journal of Economics*, Vol. 135(2): 1037–1094.

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

Caselli, Francesco and Coleman II, Wilbur John (2001). "The U.S. Structural Transformation and Regional Convergence: A Reinterpretation." *Journal of Political Economy*, Vol. 109(3): 584–616.

Chen, Edward K.Y. (1997). "The Total Factor Productivity Debate: Determinants of Economic Growth in East Asia." *Asian-Pacific Economic Literature*, Vol. 11(1): 18–38.

Chudik, Alexander and Pesaran, M. Hashem (2015). "Large Panel Data Models with Cross-Sectional Dependence: A Survey." In: Badi H. Baltagi (Editor), "The Oxford Handbook of Panel Data," (Oxford University Press).

Chudik, Alexander, Pesaran, M. Hashem and Tosetti, Elisa (2011). "Weak and Strong Cross Section Dependence and Estimation of Large Panels." *Econometrics Journal*, Vol. 14(1): C45–C90.

Coe, David T., Helpman, Elhanan and Hoffmaister, Alexander W. (1997). "North-South R&D Spillovers." *Economic Journal*, Vol. 107(440): 134–49.

Conley, T. and Ligon, E. (2002). "Economic Distance and Long-run Growth." *Journal of Economic Growth*, Vol. 7(2): 157–187.

Corden, W. Max and Findlay, Ronald (1975). "Urban Unemployment, Intersectoral Capital Mobility, and Development Policy." *Economica*, Vol. 42: 59–78.

Córdoba, Juan Carlos and Ripoll, Marla (2009). "Agriculture and aggregation." *Economics Letters*, Vol. 105(1): 110–112.

Crego, Al, Larson, Donald, Butzer, Rita and Mundlak, Yair (1998). "A new database on investment and capital for agriculture and manufacturing." Policy Research Working Paper Series 2013, The World Bank.

Dollar, David and Kraay, Aart (2004). "Trade, Growth, and Poverty." *Economic Journal*, Vol. 114(493): F22–F49.

Dowrick, Steve and Gemmell, Norman (1991). "Industrialisation, Catching Up and Economic Growth: A Comparative Study across the World's Capitalist Economies." *Economic Journal*, Vol. 101(405): 263–75.

Duarte, Margarida and Restuccia, Diego (2010). "The Role of the Structural Transformation in Aggregate Productivity." *The Quarterly Journal of Economics*, Vol. 125(1): 129–173.

Durlauf, Steven N. (1993). "Nonergodic Economic Growth." *Review of Economic Studies*, Vol. 60(2): 349–66.

Durlauf, Steven N., Johnson, Paul A. and Temple, Jonathan R.W. (2005). "Growth Econometrics." In: Philippe Aghion and Steven Durlauf (Editors), "Handbook of Economic Growth," Vol. 1 of *Handbook of Economic Growth*, chapter 8 (Elsevier), pp. 555–677.

Durlauf, Steven N., Kourtellos, Andros and Minkin, Artur (2001). "The local Solow growth model." *European Economic Review*, Vol. 45(4-6): 928–940.

Durlauf, Steven N. and Quah, Danny T. (1999). "The new empirics of economic growth." In: J. B. Taylor and M. Woodford (Editors), "Handbook of Macroeconomics," Vol. 1, chapter 4 (Elsevier), pp. 235–308.

Easterly, William (2002). *The Elusive Quest for Growth - Economists' Adventures and Misadventures in the Tropics* (Cambridge, Mass.: MIT Press).

Easterly, William and Levine, Ross (2001). "It's Not Factor Accumulation: Stylised Facts and Growth Models." *World Bank Economic Review*, Vol. 15(2): 177–219.

Eberhardt, Markus, Helmers, Christian and Strauss, Hubert (2013). "Do spillovers matter when estimating private returns to R&D?" *The Review of Economics and Statistics*, Vol. 95(2): 436–448.

Eberhardt, Markus and Presbitero, Andrea (2015). "Public debt and growth: heterogeneity and non-linearity." *Journal of International Economics*, Vol. 97(1): 45–58.

Eberhardt, Markus and Presbitero, Andrea F. (2021). "Commodity prices and banking crises." *Journal of International Economics*, Vol. 131: 103474.

Eberhardt, Markus and Teal, Francis (2011). "Econometrics for Grumblers: A New Look at the Literature on Cross-Country Growth Empirics." *Journal of Economic Surveys*, Vol. 25(1): 109–155.

Eberhardt, Markus and Teal, Francis (2013). "Structural Change and Cross-Country Growth Empirics." *World Bank Economic Review*, Vol. 27: 229–71.

Eberhardt, Markus and Teal, Francis (2020). "The Magnitude of the Task Ahead: Productivity Analysis with Heterogeneous Technology." *Review of Income and Wealth*, Vol. 66: 334–360.

Eberhardt, Markus and Vollrath, Dietrich (2018). "The Effect of Agricultural Technology on the Speed of Development." *World Development*, (109).

Echevarria, Cristina (1997). "Changes in Sectoral Composition Associated with Economic Growth." *International Economic Review*, Vol. 38(2): 431–52.

Emerick, Kyle (2018). "Agricultural productivity and the sectoral reallocation of labor in rural India." *Journal of Development Economics*, Vol. 135: 488–503.

Ertur, Cem and Koch, Wilfried (2007). "Growth, technological interdependence and spatial externalities: theory and evidence." *Journal of Applied Econometrics*, Vol. 22(6): 1033–1062.

FAO (2007). "FAOSTAT." Online database, Rome: FAO, United Nations Food and Agriculture Organisation.

Feder, Gershon (1986). "Growth in Semi-Industrial Countries: A Statistical Analysis." In: Hollis Chenery, Sherman Robinson and Moshe Syrquin (Editors), "Industrialization and Growth — A Comparative Study," (Oxford University Press), pp. 263–282.

Feenstra, Robert C, Inklaar, Robert and Timmer, Marcel P (2015). "The next generation of the Penn World Table." *American Economic Review*, Vol. 105(10): 3150–82.

Frankel, Jeffrey A. and Romer, David (1999). "Does Trade Cause Growth?" *American Economic Review*, Vol. 89(3): 379–399.

Gollin, Douglas, Parente, Stephen and Rogerson, Richard (2002). "The Role of Agriculture in Development." *American Economic Review*, Vol. 92(2): 160–164.

Greenwald, Bruce and Stiglitz, Joseph E. (2006). "Helping Infant Economies Grow: Foundations of Trade Policies for Developing Countries." *American Economic Review*, Vol. 96(2): 141–146.

Grossman, Gene M and Helpman, Elhanan (1991). *Innovation and growth in the Global Economy* (Cambridge, Mass: MIT Press).

Hall, Robert E. and Jones, Charles I. (1999). "Why Do Some Countries Produce So Much More Output Per Worker Than Others?" *Quarterly Journal of Economics*, Vol. 114(1): 83–116.

Harris, John R and Todaro, Michael P (1970). "Migration, Unemployment & Development: A Two-Sector Analysis." *American Economic Review*, Vol. 60(1): 126–42.

Hsieh, Chang-Tai and Klenow, Peter J. (2010). "Development Accounting." *American Economic Journal: Macroeconomics*, Vol. 2(1): 207–23.

Irz, Xavier and Roe, Terry (2005). "Seeds of growth? Agricultural productivity and the transitional dynamics of the Ramsey model." *European Review of Agricultural Economics*, Vol. 32(2): 143–165.

Jorgensen, Dale W. (1961). "The Development of a Dual Economy." *Economic Journal*, Vol. 71(282): 309–334.

Kaldor, Nicholas (1957). "A model of economic growth." *Economic Journal*, Vol. 67: 591–624.

Kaldor, Nicholas (1966). *Causes of the Slow Rate of Economic Growth in the United Kingdom* (Cambridge University Press).

Kapetanios, George, Pesaran, M. Hashem and Yamagata, Takashi (2011). "Panels with Nonstationary Multifactor Error Structures." *Journal of Econometrics*, Vol. 160(2): 326–348.

Klenow, Peter J. and Rodriguez-Clare, Andres (1997a). "Economic growth: A review essay." *Journal of Monetary Economics*, Vol. 40(3): 597–617.

Klenow, Peter J. and Rodriguez-Clare, Andrés (1997b). "The Neoclassical Revival in Growth Economics: Has It Gone Too Far?" *NBER Macroeconomics Annual*, Vol. 12: 73–103.

Kongsamut, Piyabha, Rebelo, Sergio and Xie, Danyang (2001). "Beyond Balanced Growth." *Review of Economic Studies*, Vol. 68(4): 869–82.

Kourtellos, Andros, Stengos, Thanasis and Tan, Chih Ming (2008). "THRET: Threshold Regression with Endogenous Threshold Variables." University of Cyprus Department of Economics Working Paper.

Kuznets, Simon (1961). "Economic Growth and the Contribution of Agriculture: Notes on Measurement." *International Journal of Agrarian Affairs*, Vol. 3(1): 56–75.

Laitner, John (2000). "Structural Change and Economic Growth." *Review of Economic Studies*, Vol. 67(3): 545–61.

Landon-Lane, John S. and Robertson, Peter E. (2007). "Reassessing The Impact Of Barriers To Capital Accumulation On International Income Differences." *International Economic Review*, Vol. 48(1): 147–154.

Levine, Ross and Renelt, David (1991). "Cross-Country Studies of Growth and Policy - Methodological, Conceptual and Statistical Problems." World Bank WPS# 608.

Lewis, W. Arthur (1954). "Economic Development with Unlimited Supplies of Labour." *The Manchester School*, Vol. 22: 139–191.

Lucas, Robert Jr. (1988). "On the mechanics of economic development." *Journal of Monetary Economics*, Vol. 22(1): 3–42.

Mankiw, N. Gregory, Romer, David and Weil, David N. (1992). "A Contribution to the Empirics of Economic Growth." *Quarterly Journal of Economics*, Vol. 107(2): 407–437.

Martin, Will and Mitra, Devashish (2002). "Productivity Growth and Convergence in Agriculture versus Manufacturing." *Economic Development and Cultural Change*, Vol. 49(2): 403–422.

Matsuyama, Kiminori (1992). "Agricultural productivity, comparative advantage, and economic growth." *Journal of Economic Theory*, Vol. 58(2): 317–334.

Matsuyama, Kiminori (2009). "Structural Change in an Interdependent World: A Global View of Manufacturing Decline." *Journal of the European Economic Association*, Vol. 7(2-3): 478–486.

Mundlak, Yair (1988). "Endogenous Technology and the Measurement of Productivity." In: Susan M. Capalbo and John M. Antle (Editors), "Agricultural Productivity: Measurement and Explanation," chapter 11 (Washington: Resources for the Future), pp. 316–331.

Mundlak, Yair, Butzer, Rita and Larson, Donald F. (2012). "Heterogeneous technology and panel data: The case of the agricultural production function." *Journal of Development Economics*, Vol. 99(1): 139–149.

Murphy, Kevin M., Shleifer, Andrei and Vishny, Robert W. (1989). "Industrialization and the Big Push." *Journal of Political Economy*, Vol. 97(5): 1003–26.

Paauw, Douglas S. and Fei, John C.H. (1973). *The Transition in Open Dualistic Economies — Theory and Southeast Asian Experience* (New Haven, CN: Yale University Press).

Pesaran, M. Hashem (2006). "Estimation and inference in large heterogeneous panels with a multifactor error structure." *Econometrica*, Vol. 74(4): 967–1012.

Pesaran, M. Hashem (2007). "A simple panel unit root test in the presence of cross-section dependence." *Journal of Applied Econometrics*, Vol. 22(2): 265–312.

Pesaran, M Hashem (2015). "Testing weak cross-sectional dependence in large panels." *Econometric Reviews*, Vol. 34(6-10): 1089–1117.

Pesaran, M. Hashem and Smith, Ron P. (1995). "Estimating long-run relationships from dynamic heterogeneous panels." *Journal of Econometrics*, Vol. 68(1): 79–113.

Pesaran, M. Hashem, Smith, Vanessa and Yamagata, Takashi (2013). "Panel Unit Root Tests in the Presence of a Multifactor Error Structure." *Journal of Econometrics*, Vol. 175(2): 94–115.

Pesaran, M. Hashem and Tosetti, Elisa (2011). "Large Panels with Common Factors and Spatial Correlations." *Journal of Econometrics*, Vol. 161(2): 182–202.

Prebisch, Raul (1984). *Pioneers in Development*, chapter Five Stages in my Thinking on Economic Development (Oxford University Press).

Ranis, Gustav and Fei, John (1961). "A Theory of Economic Development." *American Economic Review*, Vol. 51(4): 533–556.

Restuccia, Diego (2004). "Barriers to Capital Accumulation and Aggregate Total Factor Productivity." *International Economic Review*, Vol. 45(1): 225–238.

Restuccia, Diego, Yang, Dennis Tao and Zhu, Xiaodong (2008). "Agriculture and Aggregate Productivity: A Quantitative Cross-Country Analysis." *Journal of Monetary Economics*, Vol. 55(2): 234–250.

Rivera-Batiz, Luis A and Romer, Paul M (1991). "Economic Integration and Endogenous Growth." *The Quarterly Journal of Economics*, Vol. 106(2): 531–55.

Robertson, Peter E (1999). "Economic Growth and the Return to Capital in Developing Economies." *Oxford Economic Papers*, Vol. 51(4): 577–94.

Robinson, Sherman (1971). "Sources of Growth in Less Developed Countries: A Cross-Section Study." *Quarterly Journal of Economics*, Vol. 85(3): 391–408.

Solow, Robert. M. (1956). "A Contribution to the Theory of Economic Growth." *Quarterly Journal of Economics*, Vol. 70(1): 65–94.

Solow, Robert. M. (1957). "Technical Change and the Aggregate Production Function." *Review of Economics and Statistics*, Vol. 39(3): 312–20.

Swan, Trevor W. (1956). "Economic Growth and Capital Accumulation." *Economic Record*, Vol. 32(2): 334–61.

Temin, Peter (2002). "The Golden Age of European growth reconsidered." *European Review of Economic History*, Vol. 6(01): 3–22.

Temple, Jonathan (1999). "The New Growth Evidence." *Journal of Economic Literature*, Vol. 37(1): 112–156.

Temple, Jonathan (2001). "Structural Change and Europe's Golden Age." CEPR Discussion Papers 2861, C.E.P.R. Discussion Papers.

Temple, Jonathan (2003). "The Long-Run implications of Growth Theories." *Journal of Economic Surveys*, Vol. 17(3): 497–510.

Temple, Jonathan (2004). "Dualism and Aggregate Productivity." CEPR Discussion Papers #4387.

Temple, Jonathan (2005). "Dual economy models: A primer for growth economists." *The Manchester School*, Vol. 73(4): 435–478.

Temple, Jonathan and Wößmann, Ludger (2006). "Dualism and cross-country growth regressions." *Journal of Economic Growth*, Vol. 11(3): 187–228.

Timmer, C. Peter (2002). "Agriculture and economic development." In: B. L. Gardner and G. C. Rausser (Editors), "Handbook of Agricultural Economics," Vol. 2 of *Handbook of Agricultural Economics*, chapter 29 (Elsevier), pp. 1487–1546.

UNIDO (2004). "UNIDO Industrial Statistics 2004." Online database, Vienna: UNIDO, United Nations Industrial Development Organisation.

Vollrath, Dietrich (2009a). "The dual economy in long-run development." *Journal of Economic Growth*, Vol. 14(4): 287–312.

Vollrath, Dietrich (2009b). "How important are dual economy effects for aggregate productivity?" *Journal of Development Economics*, Vol. 88(2): 325–34.

Vollrath, Dietrich (2011). "The Agricultural Basis of Comparative Development." *Journal of Economic Growth*, Vol. 16(4): 343–370.

World Bank (2008). "World Development Indicators." Online Database, Washington: The World Bank.

Young, Alwyn (1995). "The Tyranny of Numbers: confronting the statistical realities of the East Asian growth experience." *Quarterly Journal of Economics*, Vol. 110(3): 641–680.

Data Appendix

A-1 Data construction

Table A-I provides details on the sample makeup. Descriptive statistics for all variables in the empirical analysis are presented in Table A-II.

Investment data Data for agricultural and manufacturing investment (`AgSEInv`, `MfgSEInv`) in constant 1990 LCU, the US$-LCU exchange rate (`Ex_Rate`, see comment below) as well as sector-specific deflators (`AgDef`, `TotDef`) were taken from Crego et al. (1998). Note that Crego et al. (1998) also provide capital stock data, which they produced through their own calculations from the investment data. Martin and Mitra (2002) recommend the use of a single year exchange rate is preferrable to the use of annual ones in the construction of real output (see next paragraph) and capital stock (see below).

Output data For manufacturing I use data on aggregate GDP in current LCU and the share of GDP in manufacturing from the World Bank World Development Indicators (WDI) (World Bank, 2008). For agriculture we use agricultural value-added in current LCU from the same source. The latter is preferred over the share of GDP in agriculture for data coverage reasons (in theory they should be the same, but they are not). The two sectoral value-added series are then deflated using the Crego et al. (1998) sectoral deflator for agriculture and the total economy deflator for manufacturing, before using the 1990 US$-LCU exchange rates to make them comparable across countries.

Note that the currencies used in the Crego et al. (1998) data differ from those applied in the WDI data for a number of European countries due to the adoption of the Euro: for the latter I therefore need to use an alternative 1990 US$-LCU exchange rate for these economies.[27]

Labour data For agriculture I adopt the variable 'economically active population in agriculture' from the FAO's PopSTAT (FAO, 2007). Manufacturing labour is taken from UNIDO's INDSTAT UNIDO (2004).

Land data The land variable is taken from ResourceSTAT and represents arable and permanent crop land (originally in 1000 hectare) (FAO, 2007).

Capital stock I construct capital stock in agriculture and manufacturing by applying the perpetual inventory method described in detail in Klenow and Rodriguez-Clare (1997b) using the investment data from Crego et al. (1998), which is transformed into US$ by application of the 1990 US$-LCU exchange rate. For the construction of sectoral base year capital stock I employ average sector value-added growth rates g_j (using the deflated sectoral value-added

[27]In detail, we apply exchange rates of 1.210246384 for AUT, 1.207133927 for BEL, 1.55504706 for FIN, 1.204635181 for FRA, 2.149653527 for GRC, 1.302645017 for IRL, 1.616114954 for ITA, 1.210203555 for NLD and 1.406350856 for PRT. See Table A-I for country codes.

data described above), the average sectoral investment to value-added ratio $(I/Y)_j$ and an assumed depreciation rate of 5% to construct

$$\left(\frac{K}{Y}\right)_{0j} = \frac{IY_j}{g_j + 0.05}$$

for sector j. This ratio is then multiplied by sectoral value-added in the base year to yield K_{0j}. Note that the method deviates from that discussed in Klenow and Rodriguez-Clare (1997b) as they use *per capita* GDP in their computations and therefore need to account for population growth in the construction of the base year capital stock.

A-2 Sample makeup and descriptives

Table A-I: Descriptive statistics: Sample makeup for all datasets

#	WBCODE	COUNTRY	OBS	#	WBCODE	COUNTRY	OBS
1	AUS	Australia	20	22	KEN	Kenya	29
2	AUT	Austria	22	23	KOR	South Korea	29
3	BEL	Belgium-Luxembourg	22	24	LKA	Sri Lanka	17
4	CAN	Canada	30	25	MDG	Madagascar	20
5	CHL	Chile	20	26	MLT	Malta	23
6	COL	Colombia	26	27	MUS	Mauritius	16
7	CYP	Cyprus	18	28	MWI	Malawi	23
8	DNK	Denmark	26	29	NLD	Netherlands	23
9	EGY	Egypt	24	30	NOR	Norway	22
10	FIN	Finland	28	31	NZL	New Zealand	19
11	FRA	France	23	32	PAK	Pakistan	24
12	GBR	United Kingdom	22	33	PHL	Philippines	24
13	GRC	Greece	28	34	PRT	Portugal	20
14	GTM	Guatemala	19	35	SWE	Sweden	23
15	IDN	Indonesia	22	36	TUN	Tunisia	17
16	IND	India	29	37	USA	United States	23
17	IRL	Ireland	23	38	VEN	Venezuela	19
18	IRN	Iran	25	39	ZAF	South Africa	26
19	ISL	Iceland	20	40	ZWE	Zimbabwe	25
20	ITA	Italy	21				
21	JPN	Japan	28			**Total**	**918**

Table A-II: Descriptive statistics

Panel (A): Variables in untransformed level terms

AGRICULTURE DATA						MANUFACTURING DATA					
Variable	**mean**	**median**	**std. dev.**	**min.**	**max.**	**Variable**	**mean**	**median**	**std. dev.**	**min.**	**max.**
Output	1.8E10	6.0E09	3.0E10	3.5E07	2.2E11	Output	7.6E10	8.8E09	2.1E11	7.2E06	1.4E12
Labour	9.6E06	1.3E06	3.5E07	3.0E03	2.3E08	Labour	1.7E06	4.8E05	3.4E06	9.6E03	2.0E07
Capital	6.5E10	1.1E10	1.5E11	2.9E07	8.6E11	Capital	1.3E11	2.0E10	3.0E11	1.4E07	1.8E12
Land	1.8E07	3.5E06	4.1E07	6.0E03	1.9E08						
in logarithms											
Output	22.39	22.51	1.73	17.38	26.13	Output	22.84	22.89	2.29	15.79	27.99
Labour	14.00	14.04	2.02	8.01	19.27	Labour	13.10	13.08	1.65	9.17	16.79
Capital	22.96	23.07	2.28	17.18	27.48	Capital	23.64	23.74	2.27	16.46	28.22
Land	15.11	15.07	1.99	8.70	19.07						
in growth rates											
Output	1.7%	1.9%	10.4%	-41.5%	53.9%	Output	4.4%	3.9%	10.1%	-40.9%	84.2%
Labour	-0.6%	0.0%	3.0%	-28.8%	13.4%	Labour	1.9%	1.1%	6.8%	-38.8%	78.1%
Capital	1.9%	1.2%	3.6%	-5.1%	31.4%	Capital	4.8%	3.6%	5.0%	-5.1%	53.0%
Land	0.1%	0.0%	2.2%	-23.1%	13.6%						

Panel (B): Variables in per worker terms

AGRICULTURE DATA						MANUFACTURING DATA					
Variable	**mean**	**median**	**std. dev.**	**min.**	**max.**	**Variable**	**mean**	**median**	**std. dev.**	**min.**	**max.**
Output	12,724	6,644	13,161	44.18	57,891	Output	27,093	20,475	22,111	753	101,934
Capital	52,367	9,925	63,576	13.10	222,397	Capital	63,533	43,577	64,557	1,475	449,763
Land	9.66	3.00	20.34	0.29	110						
in logarithms											
Output	8.39	8.80	1.83	3.79	10.97	Output	9.74	9.93	1.09	6.62	11.53
Capital	8.96	9.20	2.71	2.57	12.31	Capital	10.54	10.68	1.09	7.30	13.02
Land	1.11	1.10	1.41	-1.24	4.70						
in growth rates											
Output	2.3%	2.5%	10.5%	-43.7%	56.0%	Output	2.5%	2.5%	9.0%	-67.0%	73.0%
Capital	2.5%	2.0%	4.2%	-7.8%	31.1%	Capital	2.9%	2.9%	6.6%	-71.7%	42.4%
Land	0.7%	0.5%	3.4%	-18.4%	28.8%						

Notes: We report the descriptive statistics for value-added (in US$1990), labour (headcount), capital stock (same monetary values as VA in each respective dataset) and land (in hectare) for the regression sample ($n = 918$; $N = 40$).

Technical Appendix — not for publication

TA-1 Time-series properties

Table TA-I: Second generation panel unit root tests

PANEL (A): AGRICULTURE DATA

	Variables in levels							*Variables in growth rates*					
	log VA pw		**log Labour**		**log Cap pw**			**VA pw**		**Labour**		**Cap pw**	
lags	Ztbar	p	Ztbar	p	Ztbar	p	lags	Ztbar	p	Ztbar	p	Ztbar	p
0	-0.93	0.18	7.88	1.00	7.14	1.00	0	-16.11	0.00	1.01	0.84	-1.63	0.05
1	-1.25	0.11	5.94	1.00	3.03	1.00	1	-10.88	0.00	2.66	1.00	-1.10	0.14
2	2.23	0.99	7.65	1.00	4.78	1.00	2	-5.82	0.00	5.94	1.00	3.49	1.00
3	4.18	1.00	9.18	1.00	4.80	1.00	3	-2.09	0.02	6.64	1.00	4.48	1.00
	Land pw							**Land pw**					
lags	Ztbar	p					lags	Ztbar	p				
0	9.15	1.00					0	-10.40	0.00				
1	6.34	1.00					1	-3.05	0.00				
2	5.48	1.00					2	-0.17	0.43				
3	3.42	1.00					3	2.65	1.00				

PANEL (B): MANUFACTURING DATA

	Variables in levels							*Variables in growth rates*					
	log VA pw		**log Labour**		**log Cap pw**			**VA pw**		**Labour**		**Cap pw**	
lags	Ztbar	p	Ztbar	p	Ztbar	p	lags	Ztbar	p	Ztbar	p	Ztbar	p
0	0.57	0.72	2.05	0.98	1.61	0.95	0	-18.64	0.00	-11.52	0.00	-9.27	0.00
1	1.69	0.95	1.12	0.87	0.28	0.61	1	-9.58	0.00	-7.76	0.00	-5.71	0.00
2	1.68	0.95	3.52	1.00	1.62	0.95	2	-4.61	0.00	-4.36	0.00	-2.94	0.00
3	3.00	1.00	3.08	1.00	2.75	1.00	3	-1.50	0.07	-0.81	0.21	0.23	0.59

Notes: We report test statistics and p-values for the Pesaran (2007) CIPS panel unit root test of the variables in our four datasets. In all cases we use $N = 40$, $n = 918$ for the levels data. 'Lags' refers to the augmentation with lagged dependent variables (Augmented Dickey-Fuller test).

TA-2 Cross-section dependence

Table TA-II: Cross-section correlation analysis

	Variables in levels				*Variables in FD*			
AGRICULTURE	$\bar{\rho}$	$\|\bar{\rho}\|$	CD	(p)	$\bar{\rho}$	$\|\bar{\rho}\|$	CD	(p)
log VA pw	0.33	0.51	42.42	0.00	0.05	0.23	6.32	0.00
log Labour	0.00	0.80	0.94	0.35	0.07	0.56	8.55	0.00
log Capital pw	0.41	0.71	51.52	0.00	0.08	0.41	8.86	0.00
log Land pw	0.02	0.67	3.57	0.00	0.02	0.29	2.91	0.00
MANUFACTURING	$\bar{\rho}$	$\|\bar{\rho}\|$	CD	(p)	$\bar{\rho}$	$\|\bar{\rho}\|$	CD	(p)
log VA pw	0.39	0.59	49.87	0.00	0.05	0.22	6.19	0.00
log Labour	0.15	0.62	18.98	0.00	0.14	0.26	17.31	0.00
log Capital pw	0.59	0.76	74.15	0.00	0.07	0.22	8.01	0.00

Notes: We report the average correlation coefficient across the $N(N-1)$ variable series $\bar{\rho}$, as well as the average absolute correlation coefficient $|\bar{\rho}|$. CD is the formal cross-section correlation tests introduced by Pesaran (2015). Under the H_0 of cross-section independence its statistics is asymptotically standard normal. We use our regression sample $N = 40$, $n = 918$ for the levels data. The same sample is used for the first difference data, where $n = 884$.

TA-3 Additional tables

Table TA-III: Computed TFP-growth rates (average %age rate per annum)

				Agriculture								Manufacturing							
				M&M		2FE		CCEP		CMG		M&M		2FE		CCEP		CMG	
#		Country	obs	[1]		[2]		[3]		[4]		[5]		[6]		[7]		[8]	
1	AUS	Australia	28	1.96		0.29	▼	0.07	▼	-1.01	▼	-1.07		2.22		1.51		1.53	
2	AUT	Austria	22	0.90		3.82		4.54		4.63		-0.09		2.16		1.39		1.39	
3	BEL	Belgium-Lux.	27	0.76		2.60		2.90		2.86		2.18		3.30		4.50		4.54	
4	CAN	Canada	29	0.37		2.98		2.34		2.29		0.88		2.04		1.90		1.83	
5	CHL	Chile	28	1.23		1.16		0.47		0.33		2.28		5.10	△	5.56	△	5.55	△
6	COL	Colombia	21	2.64		2.61		3.30		3.35		0.88		1.59		1.95		1.97	
7	CYP	Cyprus	20	-1.83	▼	5.29	△	5.93	△	5.86	△	-1.52	▼	0.84		0.27	▼	0.25	▼
8	DNK	Denmark	22	0.68		1.97		1.58		1.86		0.49		2.04		1.02		1.02	
9	EGY	Egypt	21	0.99		3.37		4.23		4.13		1.97		3.35		3.72		3.70	
10	FIN	Finland	22	-1.95	▼	2.60		2.31		2.18		0.44		1.47		2.19		2.20	
11	FRA	France	19	-0.25		3.33		3.18		3.24		1.84		1.62		3.31		3.31	
12	GBR	United Kingdom	19	3.97	△	0.52		0.20		0.20		0.22		2.42		1.96		1.73	
13	GRC	Greece	23	2.85		4.52	△	6.13	△	6.31	△	2.04		3.32		4.76		4.77	
14	GTM	Guatemala	25	0.88		1.60		1.20		1.24		0.23		1.22		0.82		0.84	
15	IDN	Indonesia	23	2.13		1.97		0.75		0.84		2.67	△	3.30		4.66		4.39	
16	IND	India	21	-0.38	▼	1.52		1.18		1.38		1.84		2.10		2.95		2.97	
17	IRL	Ireland	21	1.04		4.28		5.32	△	5.64	△	2.52		3.40		5.98	△	5.78	△
18	IRN	Iran	16	0.62		1.78		2.80		2.18		0.06		-0.71	▼	0.70		0.88	
19	ISL	Iceland	18	-1.18	▼	2.13		4.29		4.94		0.27		2.85		2.50		2.51	
20	ITA	Italy	16	3.25	△	1.20		-0.32	▼	-0.25	▼	-1.18	▼	1.42		0.75		0.96	
21	JPN	Japan	27	2.74		4.33	△	3.72		3.85		0.37		4.13		3.71		3.95	
22	KEN	Kenya	28	0.79		1.73		1.79		1.91		0.75		2.87		2.15		2.32	
23	KOR	South Korea	22	2.79		5.49	△	4.11		3.82		2.58	△	6.83	△	6.41	△	6.37	△
24	LKA	Sri Lanka	18	0.50		0.15	▼	0.13		0.36		-1.85	▼	0.95		-0.17	▼	0.05	▼
25	MDG	Madagascar	19	-0.50	▼	-0.09	▼	-0.95	▼	-1.07	▼	-2.74	▼	-2.38	▼	-2.76	▼	-2.76	▼
26	MLT	Malta	22	3.49	△	7.03	△	7.58	△	7.57	△	5.25	△	4.85	△	7.55	△	7.43	△
27	MUS	Mauritius	24	1.59		1.61		1.95		2.18		-2.43	▼	0.04		-0.78	▼	-0.66	▼
28	MWI	Malawi	22	1.40		2.05		2.70		2.53		1.39		8.25	△	8.52	△	8.54	△
29	NLD	Netherlands	27	0.18		1.68		1.96		1.73		0.88		2.34		2.09		2.10	
30	NOR	Norway	25	3.21	△	2.43		2.47		2.56		0.94		2.05		2.15		2.07	
31	NZL	New Zealand	22	0.39		0.07	▼	-0.04	▼	0.05	▼	0.65		2.95		2.55		2.48	
32	PAK	Pakistan	24	0.82		1.78		2.38		2.39		0.92		3.39		3.67		3.65	
33	PHL	Philippines	25	0.05		2.39		1.30		1.66		-0.75		1.70		0.51	▼	0.50	▼
34	PRT	Portugal	19	-0.34		4.24		5.79	△	5.70	△	2.81	△	4.22	△	5.00		5.27	
35	SWE	Sweden	17	2.39		2.30		1.89		1.85		1.07		-0.68	▼	1.67		2.03	
36	TUN	Tunisia	21	0.51		3.10		3.98		3.99		0.01		2.30		1.03		1.09	
37	USA	United States	23	0.32		0.45		-0.84	▼	-0.65	▼	-0.88		0.02	▼	1.05		0.99	
38	VEN	Venezuela	18	1.72		2.20		2.12		2.16		0.09		1.04		0.96		1.13	
39	ZAF	South Africa	15	2.76		1.54		1.19		1.20		1.64		-1.42	▼	1.54		1.55	
40	ZWE	Zimbabwe	19	3.76	△	-0.13	▼	0.37		0.69		3.18	△	4.16		4.52		4.63	
		Robust mean		1.18		2.19		2.31		2.32		0.86		2.29		2.44		2.45	
		[t-statistic]		[4.66]		[8.57]		[6.92]		[6.79]		[3.34]		[8.33]		[6.76]		[6.84]	

Notes: For each empirical model we indicate the five countries with the highest TFP growth rates with △ and the five countries with the lowest TFP growth rates with ▼. M&M refers to the approach using country-specific linear trends in a common technology model (Martin and Mitra, 2002).