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LINKAGES AND ECONOMIC DEVELOPMENT

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ABSTRACT

Specialization is a powerful source of productivity gains, but how production networks at the industry level are related to aggregate productivity in the data is an open question. We construct a database of input-output tables covering a broad spectrum of countries and times, develop a theoretical framework to derive an econometric specification, and document a strong and robust relationship between the strength of industry linkages and aggregate productivity. We then calibrate a multisector neoclassical model and use alternative identification assumptions to extract an industry-level measure of distortions in intermediate input choices. We compute the aggregate losses from these distortions for each country in our sample and find that they are quantitatively consistent with the relationship between industry linkages and aggregate productivity in the data. Our estimates imply that the TFP gains from eliminating these distortions are modest but significant, averaging roughly 10% for middle and low income countries.

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1 Introduction

A single Honda automobile is made of 20,000 to 30,000 parts produced by hundreds of different plants and firms.[1] The maverick vision of Henry Ford, whose dream of total self-sufficiency in the production of automobiles was embodied in the massive River Rouge plant,[2] proved to be out of step with the course of economic history. Instead, the immense productivity gains of the past several centuries have relied on an extensive division of labor across plants which trade specialized inputs with one another in convoluted networks. Some key unanswered questions are how and why these networks of plants and flows of intermediates vary across countries, and how they are related to economic development.

An early literature (e.g. Hirschman (1958)) reasoned these industry linkages were essential for economic development and focused on how to promote the formation of robust input markets in poor countries and target investment to the industries with the strongest linkages. However, before the data and methods to test these ideas became available, one-sector models that abstracted from intermediate goods altogether became the standard framework for studying growth. Recent work by Ciccone (2002), Acemoglu et al. (2007), Jones (2011a) and others has shown that distortions in input markets can in principle explain a large fraction of productivity differences between countries, but this literature has remained largely theoretical. We build on these recent studies and analyze the empirical relationship between linkages and aggregate productivity.

In the first step, we develop a simple neoclassical framework in the spirit of Jones (2011a) to link the observed input-output structure of the economy to technological constraints as well as various distortions in input and output markets. These distortions diminish the gains from using intermediate inputs, make linkages weaker, and reduce measured productivity and other key indicators of development and welfare. We use the framework to derive an econometric

[1] Source: http://world.honda.com/CSR/partner.

[2] "Located a few miles south of Detroit at the confluence of the Rouge and Detroit Rivers, the original Rouge complex was a mile-and-a-half wide and more than a mile long. The multiplex of 93 buildings totaled 15,767,708 square feet of floor area crisscrossed by 120 miles of conveyors. There were ore docks, steel furnaces, coke ovens, rolling mills, glass furnaces and plate-glass rollers. Buildings included a tire-making plant, stamping plant, engine casting plant, frame and assembly plant, transmission plant, radiator plant, tool and die plant, and, at one time, even a paper mill. A massive power plant produced enough electricity to light a city the size of nearby Detroit, and a soybean conversion plant turned soybeans into plastic auto parts. The Rouge had its own railroad with 100 miles of track and 16 locomotives. A scheduled bus network and 15 miles of paved roads kept everything and everyone on the move. . . . In 1992 the only car still built at the Rouge, the Ford Mustang was about to be eliminated and assembly operations in Dearborn Assembly terminated." http://www.thehenryford.org/rouge.

specification and a summary measure of distortions based on input-output tables, as well as pinpoint identification challenges and potential solutions to these challenges.

A central ingredient of the framework is the input-output table. In a massive data effort, we have constructed a novel database of input-output tables for 106 countries at different levels of development (from Uganda to USA) and in different time periods (from 1950s to present). For example, our database includes such rare gems as input-output tables for Peru in 1955, Bangladesh in 1960 and Ghana in 1965. As we show in the paper, the broad time-series and cross-sectional coverage is essential for identifying the systematic relationship between linkages and development. These input-output tables come from national statistical offices and central banks, various international statistical agencies (e.g., OECD, Eurostat, United Nations), and academic/commercial initiatives (e.g., Global Trade Analysis Project (GTAP)).

We show that the strength of linkages — measured as the average output multiplier (AOM) from an input-output table — is strongly and positive related to measured output per worker and total factor productivity. Linkages are quantitatively important: a one standard deviation increase in AOM is associated with a 15% - 35% increase in output per worker depending on the specification, most of which stems from gains in productivity rather than accumulated factors of production. We subject this result to a battery of robustness checks. We consider additional controls and subsamples, use methods robust to outliers, exploit the panel dimension of the data, allow for nonlinear effects, and utilize alternative measures of linkages. Although there is some variation in the estimated strength of the relationship, the qualitative and quantitative results largely survive these checks. As a part of this robustness analysis, we also shed new light on why previous attempts to empirically relate linkages and productivity have been unsuccessful.

While cross-country regressions are subject to doubts about omitted variables and measurement issues, we can evaluate our findings using a calibrated version of our model and a more structural approach to identifying distortions. We use the IO data and two different identifying assumptions to extract industry-level distortions for each country, then compute the productivity gains associated with eliminating these distortions. We find that eliminating distortions would result in gains of roughly 6-10% for the median country in the sample, rising to 13-20% for countries at the 75$^{\text{th}}$ percentile and higher for a significant number of poor countries.

These gains are broadly in line with the quantitative relationships we found in the country-level regressions. When we regress the model-implied TFP on AOM, we estimate slope coefficients similar to those we found in the data. The results indicate that the data is both qualitatively and quantitatively consistent with the hypothesis that distortions in intermediate goods account for a modest but tangible fraction of cross-country variation in productivity. This finding challenges the view that intermediate goods linkages can be neglected when studying the process of economic development. At the same time, our results do not support the view that distortions in intermediate goods markets are the primary cause of low productivity in poor countries.

Our paper contributes to the reviving literature on intermediate goods linkages and economic development. In growth theory the seminal work of Romer (1987, 1990) and Grossman and Helpman (1992) formalized the idea that the division of labor, modeled as an increasing variety of intermediate products, could generate sustained economic growth. More recently, Acemoglu et al. (2007) study how contractual incompleteness affects the range of intermediate inputs used in production and consequently an economy's overall productivity. They show that a greater level of contractual incompleteness reduces the number of intermediate inputs used in production, with greater reductions when intermediate inputs are more complementary in production. Jones (2011a) shows how distortions that act like taxes on final output reduce intermediate usage and how relatively modest distortions might reduce TFP substantially through this channel.[3] Our paper focuses on quantifying the effects of the frictions identified by Acemoglu et al. (2007) and Jones (2011a) empirically in a general macroeconomic framework. To the best of our knowledge, our paper is the first broad cross-country study of intermediate linkages and development since Chenery et al. (1986).

Our paper is also related to the large literature on the fragmentation of production and the boundaries of the firm, much of which has been written in the context of international trade.[4] Grossman and Helpman (2002) analyze the firm's decision to vertically integrate production in a general equilibrium model with many industries in a search and matching model with specialized intermediate suppliers. Their model features multiple equilibria with different industry structures evolving in *ex ante* identical countries due to the negative externality that a firm's decision to vertically integrate exerts by thinning the market for intermediate inputs. Costinot (2007), Nunn (2007) and Levchenko (2007) show that differences in contractual institutions are a source of comparative advantage: countries with poor institutions are net importers of contract-intensive products. Topalova and Khandelwal (2011) find that access to imported intermedi-

[3]For a recent theoretical contribution analyzing the endogenous formation of an input network and aggregate productivity, see Oberfield (2013).

[4]For a review see Antràs and Rossi-Hansberg (2009)

ate inputs improved productivity following India's trade liberalization. Boehm (2013) uses a structural model of interindustry trade and a novel measure of contract enforcement costs by industry-pair to estimate the gains from eliminating these costs for a large number of countries, and finds them to be substantial. Acemoglu et al. (2009) study the relationship between contract enforcement, financial development and vertical integration and find that high contracting costs and high financial development are associated with high degrees of vertical integration. In comparison to this literature our paper takes a broader view of the distortions that can affect trade across establishments as well as firms *within* countries and focuses on how these distortions affect aggregate productivity in a general macroeconomic framework.

Finally, our paper contributes to the literature on development accounting inaugurated by Hall and Jones (1999) and reviewed by Caselli (2005) and Hsieh and Klenow (2010). This literature typically finds that differences in TFP account for a large fraction of differences in output per worker across countries. A source of these TFP differences can be microeconomic distortions that induce misallocation of resources across firms and sectors (Restuccia and Rogerson, 2008; Hsieh and Klenow, 2009). Restuccia et al. (2008), Vollrath (2009) and Gollin et al. (2012) find that productivity in developing countries is much lower in agriculture than in non-agriculture, consistent with productive factors (including intermediate inputs to agriculture) being significantly misallocated across sectors. Our paper studies the misallocation of intermediate inputs empirically. More broadly, our paper is also related to the literature on economic growth and structural change (Imbs and Wacziarg, 2003; Duarte and Restuccia, 2010; Hausmann and Hidalgo, 2011; Buera et al., 2011). Rather than study how the composition of output changes over the course of development as in most of the literature, we study how the composition and structure of inputs changes as economies develop. The evolution of intermediate linkages over the course of development appears to be a neglected aspect of structural change that also promises to shed light on international differences in productivity.

2 Theory

Input-output (IO) tables measure the flow of intermediate products used in production between different plants or establishments, both within and between sectors. The ijth entry of the IO table $\mathbf{D}$ is the value of output from establishments in industry i that is purchased by different establishments in industry j for use in production. The iith entry is similarly defined as the value of industry i' output that is purchased by *different* establishments within industry i and used in production by industry i. Intermediate output must be traded between establishments in order to be recorded in $\mathbf{D}$. For example, if one plant produces tires and ships them to a different plant that produces finished autos, the value of the tires would be recorded in $\mathbf{D}$. If instead the same plant produced both tires and finished autos, the value of the tires would not be recorded in $\mathbf{D}$. Even though total value added is the same in both cases, the recorded flows of intermediate inputs are different.[5]

If we divide each column j of $\mathbf{D}$ by the gross output in industry j we obtain the *technical matrix* $\mathbf{B}$, which provides a summary of the linkages between different production units in the economy. Larger entries in $\mathbf{B}$ indicate a greater amount of input trade between plants. In this sense $\mathbf{B}$ measures the fragmentation of the production chain across different locations, or the level of specialization across plants in the economy, for a given production process.

There are a least two channels through which the IO structure of the economy could be related to economic development. One channel, identified by Jones (2011a,b), is through a distortion that acts like taxes on firms' final output. These could be not only sales or other formal taxes on output but also a wide range of other mechanisms such as theft, bribery, regulations, or other types of expropriation that reduce the value the firm receives from producing a given level of output. Jones (2011a) shows that these types of distortions are amplified by intermediate goods linkages between firms and result in reduced intermediate usage and lower aggregate TFP.

A second connection is through distortions that specifically affect the ability of production units to reliably source inputs from other production units in different locations and under different ownership. Hirschman (1958) and other early development theorists focused on this possibility, arguing that modern industry requires a network of mutually dependent suppliers in a variety of different sectors and that coordination failures could prevent the emergence of such a network. In addition to coordination failures, poor transportation and communication networks could impede the spatial fragmentation of production by increasing transportation and monitoring costs. As emphasized by the property rights approach to the boundaries of the firm, poor contract enforcement and other aspects of institutional environments that make transact-

[5]In theory, the ownership structure of the economy is irrelevant to whether transactions are counted as intermediate flows. Shipments between plants that are owned or controlled by the same organization are supposed to be recorded in the same manner as shipments between plants under different ownership. In practice, however, there is likely to be a strong correlation between measured flows across establishments and actual flows across firms for two reasons. First, most firms operate single establishments, so transactions across establishments are likely to be transactions between firms as well. Second, non-market transactions between establishments in the same firm are probably less likely to be recorded than market transactions between firms.

ing across firms difficult and expensive provide incentives to keep the production chain within the firm. These factors increase the range of tasks performed in an individual plant, which reduces both the size of the IO coefficients and the productivity gains from specialization across plants. High cost or unavailability of credit could also prevent the optimal use of intermediate goods. We model these two channel as an implicit tax on intermediate inputs.[6]

2.1 Basic Framework

We can use a simple model to illustrate how these forces affect the entries in the IO table. Suppose the representative firm in sector j hires labor, rents capital and purchases intermediate inputs to produce its output using the production function

$$Y_j = \left(K_j^{\alpha}\left(A_j L_j\right)^{1-\alpha}\right)^{1-\sigma_j} \cdot \prod_{i=1}^{n} X_{ij}^{\sigma_{ij}} \tag{1}$$

where the X_{ij} are the intermediate goods from sector i used by sector j and $\sigma_j = \sum_{i=1}^{n} \sigma_{ij}$, K is capital, L is labor, and A is the labor augmenting technology level. The firm sells its output to both other firms and consumers on a competitive market. However, the firm faces a "tax" of τ_j^Y percent on each unit of output it produces. It also faces a tax τ_{ij}^X on each unit of inputs that it purchases from sector i. As in Hsieh and Klenow (2009), τ^X and τ^Y represent the effect of a host of complex microeconomic distortions that could affect input and output markets.[7] In the context of our discussion above, τ^Y captures the first connection between IO structure and economic development and τ^X captures the second connection.

The firm's maximization problem is

$$\max_{K_j, L_j, X_{ij}} (1-\tau_j^Y) P_j Y_j - w L_j - r K_j - \sum_{i=1}^{n} (1+\tau_{ij}^X) P_i X_{ij} \tag{2}$$

The firm's first order condition with respect to X_{ij} can be rearranged to yield the ijth entry of the

[6] These two channels do not exhaust the list of possibilities. For example, input-output structure and economic development could be connected via the adoption of different production technologies or products which are more or less intermediate intensive. The direction of this effect on the IO coefficients is ambiguous. On the one hand, new technologies or products may be more complex in the sense of requiring a larger range of specialized inputs, increasing the average size of the IO coefficients. On the other hand, new technologies are likely to economize on expensive primary inputs such as electricity, fuel and raw materials by increasing efficiency and substituting less expensive materials.

[7] This specification of intersectoral trade costs is akin to the iceberg trade costs commonly used in models of international trade and economic geography. More explicit but stylized models of input markets and linkages can be found in Acemoglu et al. (2007), Boehm (2013) and Oberfield (2013).

(observed) IO matrix $\mathbf{B} = \{b_{ij}\}$

$$b_{ij} \equiv \frac{P_i X_{ij}}{P_j Y_j} = \frac{\sigma_{ij}}{t_{ij}} \tag{3}$$

where $t_{ij} \equiv \frac{1+\tau^X_{ij}}{1-\tau^Y_j}$. Distortions that act as taxes on revenue or intermediate input usage reduce the size of the input-output coefficient.[8] This makes statistics based on the IO entries potentially powerful indicators of the presence of distortions in the economy. However, we cannot distinguish between these two types of distortions based on the entries of $\mathbf{B}$ because they have the same effect on the IO coefficient. Furthermore, without additional information we cannot separate the technological factor share σ_{ij} from the distortion, even in the special case of the Cobb-Douglas production function. We will return to this point below, but first we examine how distortions affect productivity.

2.2 Distortions and Productivity

First consider an economy with only one sector and hence only one intermediate input. Substituting the firm's first order condition back into the production function, solving for output and subtracting intermediate inputs gives an expression for value added or net output,

$$VA = Y - X = K^\alpha L^{1-\alpha} \underbrace{\left[A^{1-\alpha}\left(\frac{\sigma}{t}\right)^{\frac{\sigma}{1-\sigma}}\left(1-\frac{\sigma}{t}\right)\right]}_{\text{TFP}} \tag{4}$$

where the term in brackets is measured TFP under conventional development accounting techniques that ignore intermediate goods. Measured TFP has an additional component due to intermediate goods and the distortions, and both types of distortions have identical effects. TFP is maximized when $t = 1$.[9] Notice that taxes need not be zero to achieve this maximum because exactly offsetting sales and intermediate taxes will result in no change in TFP. In the long run distortions have an additional effect on output per worker through their effect on capital accumulation.

In a multisector generalization of this model with Cobb-Douglas production functions and preferences and competitive input and output markets, Jones (2011b) shows that the aggregate

[8]This conclusion holds more generally (e.g. for CES production functions). See Appendix A for the CES formulas.

[9]See Appendix A and Jones (2011b) for derivations and more details.

(value-added) production function is Cobb-Douglas and that TFP can be written as

$$TFP = A \cdot \epsilon(\mathbf{T}, \mathbf{B}^*, \gamma, \alpha, \eta) \tag{5}$$

where A is an aggregate technology term, $\mathbf{T}$ is a matrix of sectoral distortions, $\mathbf{B}^*$ is the matrix of undistorted intermediate shares σ_{ij} (that is, $\mathbf{B}^* = \{b^*_{ij}\} = \{\sigma_{ij}\}$), γ is a vector of value-added shares, α is a vector of sectoral capital exponents and η is a vector of idiosyncratic sectoral productivities. As in the one-sector case, measured TFP is log separable in an aggregate technology term A and a term involving distortions, ϵ.[10]

There are three additional implications of this model that we want to highlight here. First, the impact of distortions on productivity is highly non-linear: distortions become increasingly costly as t moves farther from 1. Second, the productivity losses from distortions are bigger when the intermediate shares σ_{ij} are larger. Third, in the multisector model increased variability of distortions also negatively affects productivity, which is a direct consequence of the non-linear effect of distortions on productivity.

2.3 Identification

The theory above gives simple and clear predictions for how distortions affect productivity, but testing the theory and quantifying the presence and impact of these distortions in the data is challenging for several reasons. One concern is that the simple linkage between distortions and the IO coefficients in equation (3) relies on the assumptions of Cobb-Douglas technology and competitive input markets. For example, if the elasticity of substitution between factors of production is different than one, relative prices (which we do not observe) will also enter into the expression for the IO coefficient. Models with a low elasticity of substitution (Jones, 2011a) can also generate large productivity losses from relatively modest distortions, in contrast to the Cobb-Douglas model in which the losses are smaller for the same level of distortions.[11] The

[10] See Appendix A for the exact expression for ϵ.

[11] Jones (2011a) studies a model in which the elasticity of substitution between the aggregate intermediate good and the other factors of production is equal to 1, but intermediate varieties combine with non-unit elasticity of substitution. In this model, a lower elasticity of substitution magnifies the output losses from distortions. In Appendix A we show that a lower elasticity of substitution between the aggregate intermediate and the other factors of production also tends to magnify the impact of distortions for *reasonable* values of the elasticity. However, for very low elasticities of substitution the sign of this relationship is reversed. In the limit of a Leontieff aggregate production technology, moderate distortions cause no output losses. We thank Susanto Basu for making this last point to us.

exact relationship between the size of frictions, the observed IO coefficients and the impact on productivity depend on the details of the model. However, alternative models (e.g. Grossman and Helpman 2002; Acemoglu et al. 2007; Jones 2011a; Boehm 2013) yield similar qualitative predictions in the sense that higher distortions lead to lower observed intermediate shares.

The other important concern is that the technological factor shares σ_{ij} may vary across countries, so we might have trouble distinguishing between cross-country differences in distortions and differences in technology when only the matrix **B** is observed. Variation in σ_{ij} may come from differences in product mix within industries across countries or from differences in the distribution of available ideas that generate the sectoral production technology (as in Jones (2005)). In these cases, the same underlying forces that generate the distortions (e.g. cost of contract enforcement) might be correlated with factors that influence the available technology as well. In addition, variables that determine A can also affect distortions t and vice versa. As a result, the conceptual distinction between "technology" and "distortions" can be somewhat blurry in practice.[12]

In light of these constraints, our goal in this paper is modest: to explore the extent to which the data is consistent with both the qualitative and quantitative implications of our theory. To this end, we first measure the strength of the relationship between a measure of IO linkages and productivity in the data. We then employ different assumptions to identify the distortions for each country and compute their productivity impacts using the model. Finally, we compare the relationships generating by the model (in our sample) to the same relationships in the data.

Our first approach is to run regressions based on the logarithm of productivity in equation (5), of the form

$$y_{ct} = constant + \kappa \cdot AOM_{ct} + \psi \cdot CONTROLS_{ct} + error_c \tag{6}$$

where c and t index countries and time, y is a measure of productivity (output per worker, TFP, etc.), AOM_c is a measure of IO linkages that depends on both technology and distortions, and the controls are variables that may be correlated with both output per worker and either technology

[12]Recent work by Fadinger et al. (2015) identifies distortions with measured tax rates in a smaller sample from the World Input Output Database (WIOD). Using a number of simplifying assumptions, they structurally estimate the relationship between measured taxes rates, IO structure and productivity in a neoclassical framework similar to ours. They find that the model with input-output structure has substantial additional predictive power for income per capita out of sample, and that imposing U.S. levels of tax rates on poor countries results in output gains of a few percent. Our paper finds significantly larger gains from eliminating distortions because our methods account for unreported or implicit distortions as well.

or distortions. AOM is the "Average Output Multiplier," defined as

$$AOM = \frac{1}{N}\iota^T(\mathbf{I}-\mathbf{B})^{-1}\iota \tag{7}$$

where ι is a vector of ones and N is the number of sectors. The matrix $\mathbf{L} = (\mathbf{I}-\mathbf{B})^{-1}$ is the *Leontief inverse* of the input-output matrix, which in an undistorted world would measure the elasticity of output in sector j with respect to productivity in sector i as its ijth entry, taking both direct and indirect effects into account. The AOM is then the elasticity of gross output with respect to a change in aggregate productivity.

AOM has a number of attractive features as a summary measure of linkages and distortions.[13] For example, it is increasing in σ_{ij} and decreasing in t_{ij}. It is sensitive to the position of coefficients in the IO matrix as well as their magnitude because it takes both direct and indirect effects on output into account. Distortions in sectors that are highly connected to others reduce AOM more than the same distortion in a sparsely connected industry, which has intuitive appeal as well as precise foundations in our model. Because we do not observe $\mathbf{B}^*$ and instead have to use $\mathbf{B}$ to calculate AOM, κ in equation (6) is not a structural parameter measuring the impact of distortions. Despite this limitation, we view the regression (6) as a valuable tool to summarize the empirical relationships that can be used as inputs for the theoretical model.[14]

We pursue a more structural approach in our second exercise. Specifically, we model the technology σ_{ij} directly in order to extract the distortions t_{ij} and compute the model-based productivity gains of eliminating distortions for each country. Our first identification strategy is the common assumption that the U.S. IO matrix represents the undistorted technology and computing distortions for each country as the deviations from the U.S. shares. Our second strategy

[13]One potential drawback of using AOM is that it does not take the size of the sector into account. A gross output weighted version of AOM known as the *weighted average output multiplier* ($WAOM$) can be shown to be equal to the inverse of the share of intermediate inputs, which was suggested by Jones (2011b) as a measure of distortions. However, this and other weighted measures mix information on what is produced with how it is produced, which will bias the estimates if sectoral output is correlated with economic development. For example, the correlation between output per worker and the share of output in the service sector is 0.62 in our data, but services tend to be naturally less intermediate-intensive with a mean intermediate share of 0.32 vs. 0.5 for manufacturing and 0.36 for the primary sector. Countries that produce relatively more services will have a lower $WAOM$ even if they use exactly the same production techniques as countries that produce more agricultural and manufacturing output, biasing κ downward. Consequently we use AOM in our main specifications and $WAOM$ as a robustness check.

[14]While AOM is a natural summary measure of linkages, in principle there are many other measures that might be used. Some of these other measures may well more or less correlated with productivity than AOM, depending on the specification. Using alternative measure, however, yield qualitatively similar results.

postulates that technology can vary with country and sector characteristics and we can use the variation in IO tables among rich countries to predict the undistorted IO coefficients for middle- and low-income countries. We then use the estimated model to predict the technology for poor countries and compute the resulting distortions. We feed the distortions along with the other country parameters into the model to compute the productivity gains of eliminating distortions in different sectors.

In a final step we compare the model output to the data in two ways. First, we regress the TFP generated by the model on actual AOM and compare the estimated coefficient to the one we find using TFP computed from the data. Second, we regress TFP in the data on the model-generated ϵ (calculated as in equation (5)) and compare the coefficient to the theoretical prediction of 1. While each of our strategies to identify the impact of distortions on productivity has limitations, consistent results across the various approaches provides some credibility to our interpretation of the data.

3 Data

In our empirical work we utilize an extensive, newly assembled cross-country dataset of IO tables with coverage from the 1950s to 2005. The tables are from a wide variety of sources, from large electronic collections such as the OECD to hard copies of old reports from national statistics offices. Below we describe the data in greater detail and discuss some of their limitations and how we handle them.

Our richest cross-section of IO tables comes from the Global Trade and Analysis 7 (GTAP7) project, which collected consistently defined IO tables, sectoral value added and factor shares, and sector-level trade data for a number of wealthy and developing countries in the year 2004. The tables divide the economy into 56 sectors, of which 14 are agricultural, 3 mining, 25 manufacturing, 4 utilities and construction, and 10 services.[15]. The detail on agricultural inputs is especially welcome because while many IO tables aggregate agriculture into a single sector, a large share of output is agricultural in many developing countries. However, the bulk of the sectors are in manufacturing and services, which are broadly the sectors in which we would expect the largest gains from specialization. Table 11 in Appendix B shows the countries from the GTAP7 database that we include in our sample along with their values for AOM and output per

[15] We omit the 57th sector which is imputed rent from owner-occupied housing. A list of the sectors and their 3-digit abbreviations can be found in Table 13 in Appendix B

worker in 2004.[16]

GTAP7's IO tables are built from country-level IO tables submitted by specialists in the country concerned. They subject each submission to consistency checks and ensure that the tables are "reasonable" in the sense that large deviations from standard tables can be justified. Not all submitted tables have 56 sectors; in roughly half the cases the country-level data does not support the exact level of disaggregation that GTAP7 requires. GTAP7 disaggregates the agricultural sector by using a separate country-specific agricultural IO table constructed using data from the Food and Agriculture Organization (FAO) and other sources and merging this table with the user-supplied table. For other sectors that require disaggregation, GTAP7 bases the disaggregation on a "representative" table that is averaged from the tables that do have full information. This procedure could introduce some systematic measurement error, because poor countries may be less likely to have as much sectoral detail as rich countries. However, this error would tend to make the IO structure between rich and poor countries more similar, making it less likely that we would find a relationship between aggregate productivity and IO structure.[17] The resulting collection of IO tables is consistently defined by construction and of relatively high quality.

In addition to the GTAP7 cross-section, we also assembled a novel panel of IO tables using a wide variety of sources including GTAP, the OECD, Eurostat, the UN and individual country statistical offices. Non-electronic sources were entered and checked for accuracy and consistency, and some tables were discarded because of apparent errors in the original sources. The panel is unbalanced and skewed towards Western Europe and its offshoots, especially in the early years. Nevertheless developing countries have significant representation for most time periods, and early Western observations include countries like Italy, Spain, Greece and Portugal which were significantly poorer than the leading Western economies at the time.

The tables in the panel are highly heterogeneous in the quality of their data collection and the number of sectors covered, as well as their definition of what falls under each sector. Calculations of AOM based on these tables are not comparable because less aggregated tables tend to produce larger values of AOM even if the underlying IO structure is the same. Since richer

[16]We eliminated Myanmar, Bulgaria and Nigeria from the sample due to large apparent errors in their IO tables. We also excluded Botswana and Zimbabwe from the GTAP7 sample. Botswana has an exceptionally low value of AOM for its income level due to its heavy reliance on the diamond industry. Zimbabwe has a very low level of income due to the recent deterioration of its economic environment and a medium value of AOM. Both are large outliers whose effect in the regressions tends to cancel, leaving coefficient estimates roughly roughly the same but inflating standard errors. Our main results remain statistically significant if we include these countries.

[17]See the GTAP7 website at for detailed documentation of the construction.

countries tend to have more detailed tables available, this would tend to bias our estimates upward. To ensure comparability, for the panel analysis we aggregated the IO tables into 4 broad sectors: agriculture, manufacturing, services and "other" (which includes mining, utilities and construction) before computing the linkage measures.[18] We also discard observations which are missing major sectors (e.g. mining, services) or have an inconsistent treatment of trade and transportation margins.[19] Table 12 in Appendix B identifies each table, its source, whether or not it is included in the sample and the reason for omission if applicable.

The structure of production in an economy evolves slowly, and year-on-year fluctuations in a country's IO table are likely to reflect measurement error (in part due to changes in sources) and transitory factors rather than the institutional and structural changes we are trying to capture. To address this problem we divide time into five year intervals (1960-64, 1965-69, and so on) and average observations within these intervals. In a few cases we found that tables for the same country and time period from different sources disagreed wildly, in which case we simply dropped those observations. We also drop observations for which AOM changes by more than 20% over a 5 year interval.[20] Table 1 shows the number of observations available for each 5 year interval and region of the world. The long duration of our data also helps separate the noise from the changes in fundamentals that we are interested in.

We use national accounts data from the Penn World Tables (PWT) 7.0 as well as other standard sources of cross country data on geography, institutions and technology adoption. The text accompanying the tables describes the variables and sources when they are used.

4 Empirics

4.1 Descriptive Statistics and Correlations

We begin our empirical investigation of the IO data by studying industry-level linkages and their correlation with productivity at various levels of aggregation. We analyze the GTAP7 cross-section, which permits more detailed disaggregation, then turn to the panel data.

[18]To aggregate the IO table to x by x, we simply sum the elements of the flow matrix $\mathbf{D}$ in each broad category, i.e. agriculture to agriculture, agriculture to manufacturing, etc. Formally, let $\mathbf{C}$ be the x by 56 matrix with $\mathbf{C}(1, i) = 1$ if i is an agricultural sector and 0 otherwise, $\mathbf{C}(2, i) = 1$ if i is a manufacturing sector and 0 otherwise, and so on. The new x by x aggregated matrix is $\mathbf{D}_x = \mathbf{C}\mathbf{D}\mathbf{C}^T$.

[19]Standard practice is to treat trade and transportation as sectors with their own row and column in the IO table. A number of earlier tables pulled these sectors out and simply reported their total gross output. This earlier practice does not allow us to recover IO tables necessary to calculate AOM.

[20]Our estimates are robust alternative treatments of these observations.

We aggregate each country's IO matrix from 56 to 3 industries and study the individual linkages between broad sectors of the economy. The industries are primary (agriculture, mining, utilities, construction), manufacturing (secondary), and services (tertiary). Panel A of Table 2 shows the means and standard deviations of each aggregated coefficient, with columns indicating the sector using the input and rows the producing sector. The diagonal entries tend to be the largest, a pattern that is also evident in the disaggregated data. Manufacturing and services supply a lot of inputs to all sectors, while primary inputs form a somewhat smaller proportion of the inputs for other sectors. Services and manufacturing also have strong linkages with one another; an economy composed of just services and manufacturing would have stronger linkages than any other sector pair. There is considerable variation across countries in all coefficients, especially in those involving the primary sector.

Panel B of Table 2 presents the correlation of each aggregated coefficient with aggregate log output per worker in 2004 ($RGDPWOK$ from the PWT 7.0, henceforth y). Usage of primary inputs in manufacturing and services tends to be strongly negatively correlated with y. Manufacturing and service inputs are generally positively correlated with y, with the diagonal entries as well as agriculture's use of these inputs being especially highly correlated.

These sectoral patterns largely hold at a more disaggregated level as well. Panel A of Figure 1 plots the correlation of y with each industry's diagonal coefficient, while Panel B plots the correlation with the column mean of the off-diagonal elements. The correlation with the diagonal elements is low negative for most agriculture and utilities, and highly positive for most services. Manufacturing displays the most heterogeneity, with simpler products such as vegetable oils and fats (VOL), beverage and tobacco products (B_T), leather and textiles exhibiting low correlations and the bulk of more complex products like machinery (OME), metal products (FMP), electronic equipment (ELE) and petroleum and coal products (P_C) exhibiting higher correlations. Correlations with off-diagonal backward linkages are high for agriculture, low negative for manufacturing and mixed but on average positive for services. The results for manufacturing and services reflect the strong negative relationship between the use of primary inputs and y.

The total correlation of backward linkages with y depends on the relative magnitudes of the diagonal and off-diagonal elements and their correlation with one another as well as their pairwise correlations with y. Panel C of Figure 1 shows the correlation of the column mean, this time including diagonal elements, with y. The high positive correlations for agricultural industries show that off-diagonal elements dominate, while the high positive correlations for services reflect that on and off-diagonal elements largely reinforce one another. Manufacturing overall exhibits low (but positive) correlations, with diagonal and off-diagonal elements roughly cancelling in effect. Panel D plots results for the row means for each industry (including diagonal elements), a measure of forward linkages. They confirm the results from Table 2 that usage of primary inputs is negatively correlated with productivity, while manufacturing and service inputs are positively correlated. For manufacturing we once again have a generally positive relationship between the correlation and the complexity of the product.

Rich countries use more inputs from the manufacturing and service sectors, especially from plants within their own industry. This implies that rich countries exhibit greater specialization at the plant level within these industries. This is consistent with the view that manufacturing and service inputs are more complex and more subject to contract disputes that rely on good contract enforcement mechanisms, and that rich countries have better contract enforcement mechanisms. It is also consistent with the view that advanced technologies in services and manufacturing require more specialized inputs from their own broad industry categories and less primary inputs.

We turn next to the panel data, which are aggregated in the same way as in the cross-section. Panel A of Table 3 shows the means and standard deviations of each aggregated coefficient, while Panel B shows the correlation of each coefficient with y. Sample characteristics are similar to the GTAP7 data, with the main difference being somewhat lower backward linkages for manufacturing in the panel. The correlations with y are remarkably similar across the two datasets, with the main difference being slightly higher correlations with manufacturing linkages and slightly lower with service linkages in the panel data.

We can also ask which IO coefficients are correlated with growth over time. Panel C of Table 3 shows the correlation between the residuals from regressing log output per worker and each IO coefficient on country dummies. Increases in agricultural inputs are negatively correlated while increases in service inputs are strongly positively correlated with output growth. Growth in manufacturing inputs to manufacturing are somewhat negatively correlated with output growth, which could reflect the impact of factor-saving innovation. The panel and cross-section do not paint exactly the same picture, but as we discuss in more detail in Section 4.2.2, strong relationships in the cross-section are consistent with the opposite or no relationship over time. However, both the cross-section and the panel suggest a strong dichotomy between the relationship of y with primary and secondary inputs. We might expect different results from specifications that include primary linkages from those that exclude them.

4.2 Regression analysis

While the results for the individual industries are suggestive, they do not take into account the correlations between the coefficients or the impact of indirect linkages between industries. Correlations and simple regressions also do not consider other factors that influence y and may be correlated with the strength of IO linkages. In this section we tackle these issues by using AOM calculated at the country level as our dependent variable to account for all direct and indirect linkages and by controlling for institutions, technology adoption and other determinants of aggregate productivity. We use the disaggregated 56 sector tables from GTAP7 to calculate AOM in the cross-section and aggregated 4 sector tables (agriculture, mining $+$ utilities, manufacturing and services) to calculate AOM in the panel analysis. In the following section we will compare these estimates to those obtained from the model using different assumptions to identify distortions.

4.2.1 Cross-section

The top panel of Figure 2 is a scatterplot of log output per worker y against AOM with a regression line drawn through it. There is a strong positive unconditional relationship between AOM and y, although there is significant variation in productivity for each value of the multiplier. The bottom panel of the figure shows that this relationship is present and somewhat tighter when we focus on manufacturing and service linkages only. To separate the relationship between y and AOM from potentially confounding factors, we run a series of regressions given by specification (6).

The first column of Table 4 confirms that the unconditional relationship evident in Figure 2 is strong and statistically significant at the 1% level. A standard deviation increase in AOM is associated with a roughly 35% increase in output per worker. This is a substantial effect but it could overestimate the impact of distortions on productivity due to omitted variables.

The quality of institutions is an important omitted variable because it is likely to be highly correlated with both output per worker and distortions that affect trade across firms and plants. Column 2 of Table 4 adds the average value over 1996-2008 of the Rule of Law index from Kaufmann et al. (2009) as a measure of the quality of institutions. This measure has the most comprehensive coverage of the available institutional variables and it is the most relevant for our purposes because it specifically includes contract enforcement. As expected, the inclusion of this variable reduces the estimated magnitude of κ, but it remains sizeable and highly statistically significant. It also dramatically increases the fit of the regression as measured by the R^2.

Geography may affect output per worker directly through the disease environment (Sachs, 2003) and indirectly through its correlation with colonial experience, historical state formation and other variables (Acemoglu et al., 2001). In column 3 we include distance from the equator as a proxy for these factors. In column 4 we control for openness to trade using $\frac{Imports+Exports}{GDP}$ from the PWT, which corresponds to the notion of "real openness" in Alcalá and Ciccone (2004). This variable is important for both its potential direct effect on productivity as well as the theoretical importance of the size of the market in determining the degree of specialization. The estimated coefficient κ is similar in magnitude and statistical significance to the previous specification controlling for institutions alone.

A careful examination of Figure 2 reveals that many of the countries with the highest values of AOM are current or former centrally planned economies. This raises the interesting possibility that centrally planned economies may subsidize or otherwise encourage domestic sourcing of intermediate goods, perhaps through attempts to keep entire supply chains domestic or to equalize regional incomes by dictating the location of plants in underdeveloped areas. However, the resulting increase in plant-level specialization may not be associated with the typical productivity gains. More generally, heavy government involvement in the economy may increase inefficiency. To control for this possibility we include the share of government consumption in output from the PWT as well as a dummy variable indicating whether a country has a history of central planning in column 5. As expected, the estimated κ increases somewhat.

Controlling for the quality of transportation and communication infrastructure and the level of technology will help distinguish the direct impact of these variables from their indirect impact on specialization. The index of technology adoption constructed by Comin et al. (2008) measures the intensive margin of adoption for various major technologies such as motor vehicles, telephones, personal computers and the internet. Because it measures the penetration of each technology at different points in time (e.g. telephones in 1970, PCs in 2002) it is a measure of average technology adoption over the last 40 or so years. Most of the technologies are transportation and communication technologies, and so the index also serves as an index of the average quality of transportation and communication infrastructure. The drawback is that it covers only a subset of countries in our sample.[21] Column 6 shows the results when the technology adoption and infrastructure index is included. As expected, the estimated κ is somewhat lower than previous specifications but still sizable and quantitatively significant.

The inclusion of controls roughly halves the estimated κ from the simple regression in column 1. The lowest estimate implies that a standard deviation increase in AOM is associated with a roughly 15% increase in output per worker. This reduction in magnitude is in line with our priors regarding the correlation between distortions that affect input-output relationships and other determinants of output per worker. However, the magnitude of the coefficient remains sizable. We subject these results to a battery of robustness checks in Section 4.3.

To ensure that our results are not driven by primary sector linkages, we construct an alternative measure of linkages which includes only manufacturing and services, $AOM-MS$. This alternative measure has the same interpretation as AOM for the whole economy but instead it treats the economy as consisting of only a subset of industries, illustrating the convenience of using the average output multiplier as a measure of linkages in the economy. Columns (7)-(12) of Table 4 show that using this alternative measure yields very similar results and hence our findings are not driven by the relative importance of the primary sector across countries.

Theory also predicts that barriers to specialization have a direct impact on TFP, with the standard indirect effects of changes in TFP on human and physical capital accumulation. To test this hypothesis, we follow Hall and Jones (1999) and decompose output per worker in the year 2005 as

$$y = \left(\frac{K}{Y}\right)^{\frac{\alpha}{1-\alpha}} hA \tag{8}$$

where h is human capital per worker and A is TFP. We use the perpetual inventory method to construct physical capital stocks and the data from Barro and Lee (2012) on year of schooling for the population age 25 and over to construct the stock of human capital, using the same functional form and parameters as Hall and Jones (1999) to convert years of schooling into the human capital stock. We then repeat the regression in column 6 of Table 4 using the logs of the capital to output ratio (multiplied by $\alpha/(1-\alpha)$, where we take $\alpha = 0.33$), human capital per worker and TFP as the dependent variables.

Table 5 shows the results of this exercise. The log of the capital-output ratio is positively but

[21] There is no obvious pattern to the missing observations that would bias the result in one direction or another. The results from the specifications without technology adoption are similar if one excludes observations for which the technology adoption variable is missing.

not strongly related to AOM. Human capital is more robustly related to AOM, but the bulk of the relationship between AOM and output per worker is accounted for by TFP. The pattern is similar when we use $AOM - MS$ instead of AOM. These findings are consistent with the prediction that the direct impact of distortions is on TFP. The full eventual impact of distortions on capital accumulation will not be evident until the transition to the new steady state is complete. This is especially unlikely to be true in our data, which is taken from period of fundamental transformation in transportation and communications technology as well as rapid institutional change.

4.2.2 Panel

The results from Panel C of Table 3 suggest that the historical relationship between growth in linkages and productivity may be different than in the cross-section. Theory does not unambiguously predict that growth is accompanied by an increase in specialization; a strong positive level effect is consistent with a weak or non-existent growth effect if growth takes place due to technological change rather than diminishing barriers to specialization. A positive level effect could even be consistent with a negative growth effect if new production technologies tend to economize on the use of raw materials as intermediates. Thus a panel fixed effects regression is a test of the joint hypothesis that a) distortions are important determinants of output per worker, and b) reductions in distortions have been a quantitatively significant driver of economic growth in the past several decades. This hypothesis is not implausible given advances in transportation and communication technologies and the significant institutional changes in many countries over the last 50 years.

In the first pass at the data, we estimate our baseline specification using the panel data without country fixed effects (Column 1, Table 6). In this exercise, we combine time-series and cross-sectional variation in productivity and linkages. We use Driscoll and Kraay (1998) standard errors to allow for general forms of both cross-sectional and time-series dependence of the error term. While AOM is now calculated using 4×4 IO matrices (to ensure comparability across countries and times), we continue to find point estimates of κ similar to those those based only on the cross-sectional variation and IO tables from GTAP. Since we have many more observations, the coefficient is estimated more precisely. Therefore, both datasets yield similar results and we can be reasonably confident that any differences in estimates with country fixed effects do not arise from using alternative data.

With country fixed effects (column 2), the estimated κ when AOM is the only regressor is somewhat smaller than its cross-sectional counterpart in Table 4 but is sizeable and statistically significant. Some of the decrease in the size of the estimate may be due to increased noise to signal ratio typical in panel data with fixed effects included (Griliches and Hausman (1986)). Column 3 includes those controls from Table 4 which vary over time,[22] again finding similar results as in the cross-section.

Column 4 includes decade fixed effects in addition to the controls from Column 2. While this attenuates the threat of spurious regression from common trends, it also means that we will fail to detect the impact of global trends in the reduction of barriers to specialization. The point estimate is reduced but it continues to be statistically and economically significant. Based on the results from the individual coefficient regressions in Panel B of Table 3, we conjecture that this result is largely due to the strong negative correlation between the use of agricultural inputs and economic development over time. In Columns 5 through 8 we confirm this interpretation by using a version of AOM that includes linkages from manufacturing and services only ($AOM - MS$) which has magnitude and statistical significance similar to the cross-sectional estimates.

4.3 Robustness Checks

Table 7 presents some basic robustness checks and extensions of our main specification. The first row shows the result of substituting weighted AOM ($WAOM$) for AOM with full controls. As argued in Section 2, we expect $WAOM$ to be a contaminated indicator of the level of distortions because it weights naturally intermediate-intensive sectors more heavily for poor countries than rich ones. Consistent with this logic, we find that the estimated κ is smaller than the one estimated with AOM, with similar standard errors. In the second column we use a version of $WAOM$ that only includes linkages between manufacturing and service industries, with similar results.

Row 2 includes an additional regressor: imported intermediate inputs as a share of total output in the regression. The domestic and imported intermediate shares tend to be highly negatively correlated, as documented in Figure 3, which is to be expected since domestic and

[22]The measure of institutional quality with the most comprehensive time-series and cross-sectional coverage of our sample is the Polity IV measure of democratic governance, which is not the ideal concept of institutional quality for our purposes but which should be strongly correlated with the quality of contractual institutions. In our cross-sectional sample the Rule of Law index (averaged over 1996-2008) with the Polity IV index (averaged over 1980-2008) is 0.66. Alternative measures of institutional quality do not have sufficiently long time-series dimension or cover only a relatively small set of countries.

imported inputs are substitutable. Domestic distortions induce firms to import more intermediate goods, so the domestic and imported intermediate shares contain roughly the same information about distortions. Consistent with this interpretation, including import linkages in our specifications results in high joint statistical and economic significance for the coefficients on domestic and imported linkages. However, due to the strong negative correlation between these two variables and the limited statistical power of the regressions, the magnitude and statistical significance of the individual coefficients is unstable across specifications. Because of this near collinearity, we do not include imported intermediate inputs as a share of total output in other specifications.

Row 3 excludes observations corresponding to an earlier part (pre-1970) of the sample–these observations may have larger measurement errors–to explore robustness of our results. We observe similar estimates. Row 4 excludes countries with output per worker less that \$3,000 at PPP to assess whether our results are driven by grossly underdeveloped countries. We find that this is not the case and constraining the sample to exclude very poor countries yields similar results. Row 5 reports estimates of the baseline specification only on rich, OECD countries. This is an interesting exercise because previous attempts (Jones, 2011b) to discern the contribution of IO linkages were largely based on highly developed countries for which one can easily obtain input-output tables. For these countries, we fail to find any relationship between AOM and output per worker, a result consistent with previous studies. This finding highlights the importance of having large variation in IO tables. We continue to find results similar to our baseline specification when we exclude countries with low AOM values (Row 6), which tend to be poor or resource rich countries. In similar spirit, we find that our results continue to hold when we exclude very open economies (Row 7, $(imports + exports)/GDP > 1.1$; e.g. Belgium), or small economies (Row 8, population less than 4 million; e.g. Cyprus). Rows 9 and 10 assess the sensitivity of estimates to using alternative estimation methods that are robust to outliers and influential observations. We find that using these alternative methods yields similar results.

The theory of intermediate goods distortions developed in Jones (2011a,b) predicts that the impact of distortions on productivity is highly nonlinear. The effect of distortions in the neighborhood of $t = 1$ is weak but it becomes increasingly large as t moves away from 1. Variations in AOM amongst rich countries may reflect mostly factors unrelated to productivity, while variation amongst poor and middle income countries reflects distortions. Dropping high productivity countries in the linear specification tends to increase the estimated effect, in line with this theory. More formally, we test for nonlinearity of the effect size by estimating a series of quantile regressions for the quintiles $\{0.2, 0.4, 0.6, 0.8\}$. The estimated κs decrease steadily with output per worker, with the estimates at the lowest quintile of output per worker being roughly double the estimate at the highest (coefficients not reported). However, an F-test cannot reject that the coefficients are all equal at conventional significance levels. Thus the evidence is consistent with the theory which predicts that the cost of distortions is small at low levels, but we are unable to conclude definitively that nonlinearity is present.

In summary, our cross-section and panel results show that AOM is robustly positively correlated with output per worker across countries and within countries over time. While we cannot claim to have identified the causal effect of distortions on productivity, our results are qualitatively consistent with predictions of the model described in Section 2. To assess the quantitative fit of the model and provide additional evidence on the size and productivity consequences of these distortions, we turn next to a different, more model-driven empirical strategy.

5 Quantitative Exercises

In this section we model the technology σ_{ij} directly in order to extract the distortions t_{ij} and compute the model-based productivity gains of eliminating distortions for each country. We then compare the model output to the patterns we found in the data in the previous section.

5.1 Model and Identification

We use a static closed economy version of the Long and Plosser (1983) and Jones (2011b) multisector neoclassical growth model with Cobb-Douglas production functions and preferences, competitive input and output markets, and intermediate goods distortions.[23] For simplicity, and in order to reduce the impact of measurement error in our empirical exercises, we assume each industry has a single distortion rate τ_{ic}.[24] Recall from equation (5) in Section 2 that we can write total factor productivity (and total output) in this economy as the product of two terms, only one of which is a function of distortions. We focus our attention on this term, denoted ϵ_c, which is also a function the intermediate factor shares σ_{ijc}, the capital shares of income α_{ic}, the expenditure shares γ_{ic} and the idiosyncratic productivity η_{ic} in each sector.

[23] See Appendix A for the fully specified model, and Jones (2011b) for detailed derivations.

[24] Since we cannot distinguish empirically distortions in product (τ^Y) and input (τ^X) markets and these distortions are symmetric in the static, we assume for this exercise that distortions occur in the product market. To simplify notation, we drop superscripts for τ.

For the GTAP7 sample we observe the share of value added paid to capital in each industry and the share of aggregate value added produced in each industry for each country. We calibrate the α_{ic} and γ_{ic} to equal these values. Since we do not observe industry-level productivity, we set $\eta_{ic} = 1$ for all i, c. We also observe the value added shares in the panel data, but not the capital shares. We assume that the latter do not change over time and use the capital shares from GTAP7 for the panel data as well. Using equation (3), we identify the product of the distortion and the intermediate factor shares $\sigma_{ijc}(1 - \tau_{ic})$ from the observed intermediate goods shares b_{ijc}. We use two different approaches to separately identify τ_{ic} and σ_{ijc}.

Our first approach is to assume that all countries use the same intermediate goods technology and that the U.S. is undistorted: $\sigma_{ijc} = \sigma_{ij} = b_{ij,US}\ \forall c, i, j$. Under this assumption, we extract distortions as $1 - \tau_{ic}^{US} = \sum_j b_{ijc} / \sum_j b_{ij,US}$. We refer to τ_{ic}^{US} as the U.S. technology measure of distortions. Here our assumption of a single distortion per industry allows us to aggregate all the intermediate shares when estimating the distortion for that industry. Since most entries of the IO table are zero or very small, this approach avoids the problem of dividing by zero or very small numbers which can exaggerate the size of distortions. We also capped absolute value of distortions at 0.95 for each industry, which affects very few observations and helps avoid numerical problems when computing ϵ_c.

The single technology assumption, while common and simple (see e.g. Hsieh and Klenow 2009), is quite strong. Our second approach assumes instead that the systematic variation in rich country IO tables is due to variation in the σ_{ijc} and not due to distortions; that is, $\sigma_{ijc} = b_{ijc} + \nu_{ijc}$, with ν_{ijc} i.i.d. and mean zero for the sample of rich countries.[25] With this assumption, we use the rich-country patterns in technology to predict the technology for poor countries. We estimate the following equation on the sample of rich countries (the richest 20 in the sample) alone:

$$\sum_j b_{ijc} = \nu_i + \beta_{1,s} outputshare_{ic} + \beta_{2,s} \log(population)_c + error_{ic} \tag{9}$$

where $outputshare$ is the share of country c's gross output accounted for by industry i of sector s and $population$ is country c's population. We think of $outputshare$ as controlling for systematic differences in output mix between countries that specialize more or less intensively in a product,

[25] Alternatively, we could assume a non-zero mean level of rich country-sector distortions. In that case, still assuming independence, our regression would identify the true technology parameters plus the mean level of each sector's distortion in the rich country. Our counterfactuals would then be interpreted as computing the gains from bringing poor countries up to rich country levels of distortions in each sector.

as well as measurement error in sectors with little output. Including $population$ helps control for the fact that small countries are naturally more open than large countries, without modeling international trade or the underlying reasons why small countries trade more.[26] We allow the coefficients to vary with the broad sectoral classification (primary, manufacturing, services), and use industry-time fixed effects for the application to the panel data. We then use the model to predict $\sum_j \sigma_{ijc}$ for each country and industry, and compute $1 - \tau_{ic}^{adj} = \sum_j b_{ijc}/\widehat{\sum_j \sigma_{ijc}}$. We refer to τ_{ic}^{adj} as the adjusted technology measure of distortions.

5.2 Results

Table 8 summarizes the results of these exercises for the GTAP7 cross-section. The average distortion rates and the gains from eliminating them (calculated accroding to equation 5) are quite large under the U.S. technology assumption: the average country has a 17% gain in productivity from eliminating distortions in a sample that includes many rich countries. The distribution of these gains are quite skewed, with most rich countries enjoying gains in the high single digits and the poorest countries enjoying gains of 25% or more. Both the average distortion rate and the gains from eliminating them are lower for our second identification strategy ("adjusted technology"), although many countries still experience substantial gains of 13% or more. The gains computed under the two different assumption have a .39 correlation, which is not as high as we might expect. Much of the difference is accounted for by small countries, which tend to be highly distorted under the U.S. technology assumption and much less so under the adjusted technology assumption. Panel A of Figure 4, which plots the total gains against log output per worker, shows that most of the countries with the biggest gains are small economies including very wealthy ones like Luxembourg and Belgium. The analogous plot for the adjusted technology assumption in Figure 5 shows no such pattern.

Panels C through D of Figures 4 and 5 plot the gains from eliminating distortions in the primary, manufacturing and service sectors respectively. For many countries the major gains come from eliminating distortions in the primary sector under both identification assumptions. Gains from eliminating distortions in manufacturing tend to be smaller, reflecting low value added in manufacturing for the poorest countries as well as relatively small average distortions. Elimi-

[26]Explicitly modeling international trade in intermediate inputs would be an interesting extension. However, the data requirements would be far greater, as would the the number of assumptions about parameters such as the elasticities of substitution between domestic and intermediate goods. We discuss the issue of imported intermediates further in section 4.3.

nating distortions in the service sector provides somewhat larger gains than in manufacturing. Under the U.S. technology assumption a few small and relatively wealthy countries have extremely large gains in manufacturing and services, which casts doubt on the appropriateness of the U.S. technology assumption for these countries.

Turing to the results from the panel data in Table 9, we focus on the results from the adjusted tech assumption only. They are qualitatively and quantitatively quite similar to the adjusted tech scenario in the cross-section, with the main difference being that the gains are slightly more skewed in the panel. Once again the primary sector accounts for the largest portion of the gains, followed by services and manufacturing. There is also a strong downward time trend, 2% per 5 year increment, in the gains from the primary sector (controlling for country fixed effects) while there is no clear trend in the gains from manufacturing or services.

The basic message that emerges from this exercise is that the gains from eliminating distortions are modest for many countries but can be substantial for a significant number of highly distorted economies. The largest gains accrue to very poor countries that eliminate distortions to their primary sector, primarily agriculture. This provides a potential explanation for the fact that cross-country variation in TFP is highest in agriculture (Restuccia and Rogerson, 2008).

5.3 Comparing Model and Data

In this section we compare the moments implied by our model and identified distortions to those in the data. First, we regress the model implied log(TFP) on the AOM observed in the data. If the estimated slope in this regression is similar to the estimated slope in the regression reported in Section 4, then our our reduced form empirical results can be generated by the model and the identified distortions. Since the relationship between TFP and distortions in the model is certainly causal, we can conclude that our reduced form results are consistent with a quantitatively reasonable causal relationship between productivity and distortions. Second, equation 5 indicates that measured TFP is proportional to ϵ. That is, a one percent increase in ϵ raises measured TFP by one percent. We examine if this prediction holds by regressing log(TFP) observed in the data on the ϵ implied by the model.

Panel A of Table 10 gives the results of the first exercise. The estimated coefficient of 0.46 for the US technology assumption is almost exactly the same as the coefficient of 0.45 we found in the analogous exercise in Table 5, while the adjusted technology coefficient is a significantly smaller 0.14. Note that small deviations from our assumption that U.S. or rich country distortions are identically zero can have sizable effects on these coefficients due to non-linearity. For example, assuming that all rich countries have $\bar{\tau} = 0.05$ rather than zero raises the coefficient in the regression from 0.14 to 0.36. With this in mind, the broad agreement between these two sets of regressions is reassuring for both approaches.

Panels B and C report the results of the second exercise, using log(TFP) and y respectively as the dependent variables and including the full panoply of control variables from Column 6 of Table 4 for the cross-section and panel respectively. The standard errors are quite large, especially for the adjusted technology assumption which requires that we drop a significant number of countries from the sample. However, none of the specifications allow us to reject the hypothesis that the coefficient on ϵ equal 1 at conventional significance levels, and the coefficients are larger when y is the dependent variable as they should be. While hardly dispositive, these results confirm that the calibrated model is not inconsistent with the patterns we found in the data.

Overall, the two different approaches are congruent with one another and seem to deliver similar results. One potential area of disagreement lies in the role of manufacturing and service linkages. In Section 4 we found that a version of AOM including only manufacturing and service linkages was as robustly correlated with y as the full version of AOM, but the model suggests that these sectors play a lesser role in determining the gains from eliminating distortions.[27]

5.4 Alternative interpretations

This paper has presented strong evidence that poor countries tend to have weaker domestic input-output linkages, and provided an explanation that emphasizes the role of domestic distortions in reducing both productivity and intermediate input use. While the empirical evidence is both qualitatively and quantitatively consistent with this explanation, there are other potential explanations that might generate the same pattern. While a detailed assessment of alternative models is beyond the scope of this paper, in this section we briefly discuss two potential alternatives.

In both the model and our empirical work, we focused on the domestic IO table without explicitly considering imported intermediates due to the increased data and parameter require-

[27] One possibility is that distortions in these sectors are highly correlated with the important components of primary sector distortions, although the raw correlations between average distortions in these sectors is somewhat weak. Another possibility is that manufacturing and service sector distortions are correlated with the error term in the regression. A third possibility is that the gains from eliminating distortions in these sectors is larger than the model suggests. Pursuing these hypotheses further is an interesting avenue for further research.

ments that would have entailed. However, the same positive correlation between domestic inputs and productivity that we found could be generated through imported intermediates in two possible scenarios: i) imported intermediates are substitutes for domestic intermediates and the relative price of imported intermediates is low in poor countries; ii)imported intermediates are complements with domestic intermediates and the relative price of imported intermediates is high in poor countries. The second scenario is inconsistent with recent evidence that imported and domestic intermediates are substitutes with an elasticity of substitution of 2 or greater (Antràs et al., 2014; Blaum et al., 2015). The first scenario is more plausible, although one might expect the relative price of imported intermediates to be high in poor countries given their typically higher trade costs. However, we we lack any systematic evidence on the relative price of imported vs. domestic intermediates for rich and poor countries that could allow us to determine and quantify any bias from omitting imported intermediates. Understanding the interaction between domestic and imported intermediates and productivity seems like a fruitful topic for future research.

Another potential alternative set of explanations revolves around relaxing the restriction that the sectoral production functions be Cobb-Douglas. Consider instead a CES production function in capital, labor and intermediate goods from each sector. In this framework (which again requires more data and elasticities to calibrate) relative prices also affect factor shares, and there are again two scenarios that are consistent with the positive relationship between productivity and strength of domestic IO linkages: a) the elasticity of substitution in production is less than 1, and goods that are used intensively as intermediates have lower relative prices in poor countries, or b) the elasticity of substitution is greater than 1 and goods that are used intensively as intermediates have higher relative prices in poor countries. Unfortunately there is no consensus on the magnitude of aggregate or sectoral elasticities of substitution. Similarly, we lack consistent data on the relative prices of sectoral output in rich and poor countries. However, the relative price of *investment* goods is high in poor countries (Hsieh and Klenow, 2007) and it seems likely that this would continue to hold for a broader class of intermediate goods. In addition, recent studies (e.g., Boehm et al. 2014, Atalay 2014) suggest that the elasticities of substitution between different intermediate goods, and between a composite intermediate good and value added, are lower than one. Thus, we view the available evidence as weakly pointing to a world with a low elasticity of substitution and high prices for intermediate goods in poor countries, a combination that would tend to generate a negative correlation between productivity and domestic inputs.

6 Conclusion

In a famous example, Adam Smith illustrated gains from specialization in a pin factory.[28] While his focus was on gains from specialization within a factory, further economic development proved that the scope of gains extends far beyond the boundaries of a plant or firm. For example, just in North America, Honda has a network of more than 600 direct suppliers. The history of auto industry with the rise and fall of the Ford Rouge factory demonstrates that successful firms increasingly rely on networks of suppliers scattered all over the world. The omnipresent specialization in modern economies is a genuine marvel which surely has gone beyond the wildest dreams of the famous Scottish economist.

While a great deal of empirical research has been done on specialization at the very micro level (e.g., division of labor in a pin factory) and the very macro level (e.g., international trade between countries), linkages across firms and industries within a country – i.e., the middle level – have been much less studied. Most of the analysis at this middle level is theoretical and qualitative but the predictions are clear: these linkages should play an important role in economic development and are likely to be an important source of productivity gains. Having built a database of input-output tables for a broad spectrum of countries and times, we provide evidence consistent with these predictions: countries with stronger linkages have higher productivity. This relationship is quantitatively strong and robust. We also show that the empirically observed sensitivity of productivity to the strength of linkages is in line with the results from a calibrated multisector neoclassical model.

Admittedly, we cannot completely rule out potentially confounding factors in cross-country regressions or model mispecification, and hence our findings call for more research on the workings of linkages between firms and industries. Various works in economics grapple with the importance of these linkages and specialization. For example, selling and buying goods to/from domestic foreign-owned companies as well as imports of foreign inputs appear to be associated with increased productivity of firms (e.g., Javorcik (2004), Gorodnichenko et al. (2010)). Stocks

[28]Smith wrote, "One man draws out the wire, another straights it, a third cuts it, a fourth points it, a fifth grinds it at the top for receiving the head: to make the head requires two or three distinct operations: to put it on is a particular business, to whiten the pins is another ... and the important business of making a pin is, in this manner, divided into about eighteen distinct operations, which in some manufactories are all performed by distinct hands, though in others the same man will sometime perform two or three of them."

of companies with corporate spin-offs aimed to increase the focus of their operations appear to earn higher abnormal returns relative to stocks of firms with spin-offs without such a focus (e.g., Daley et al. (1997), Desai and Jain (1999)). However, these efforts lack a unifying framework with a macroeconomic perspective. We hope that future research will take up these challenges.

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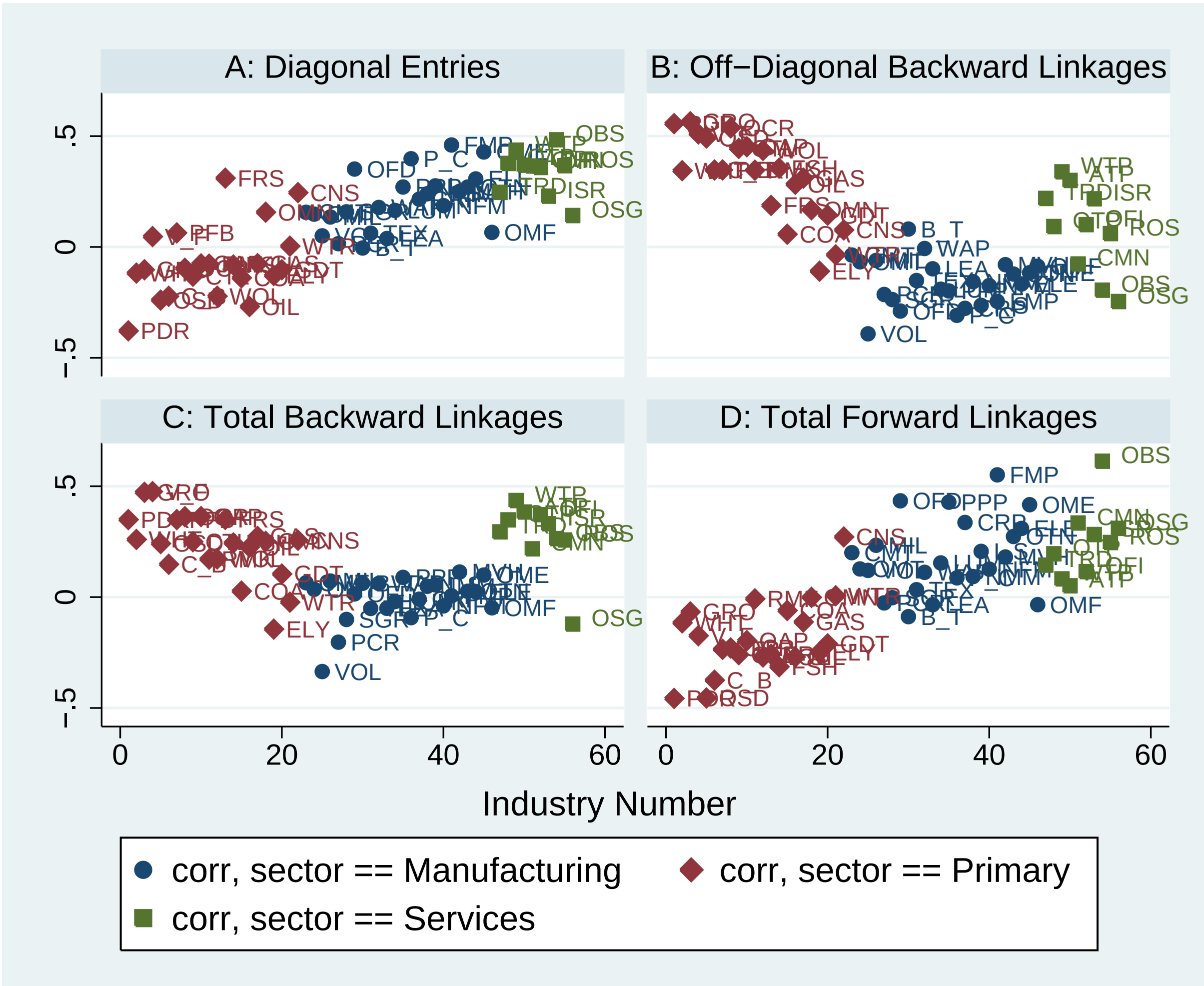
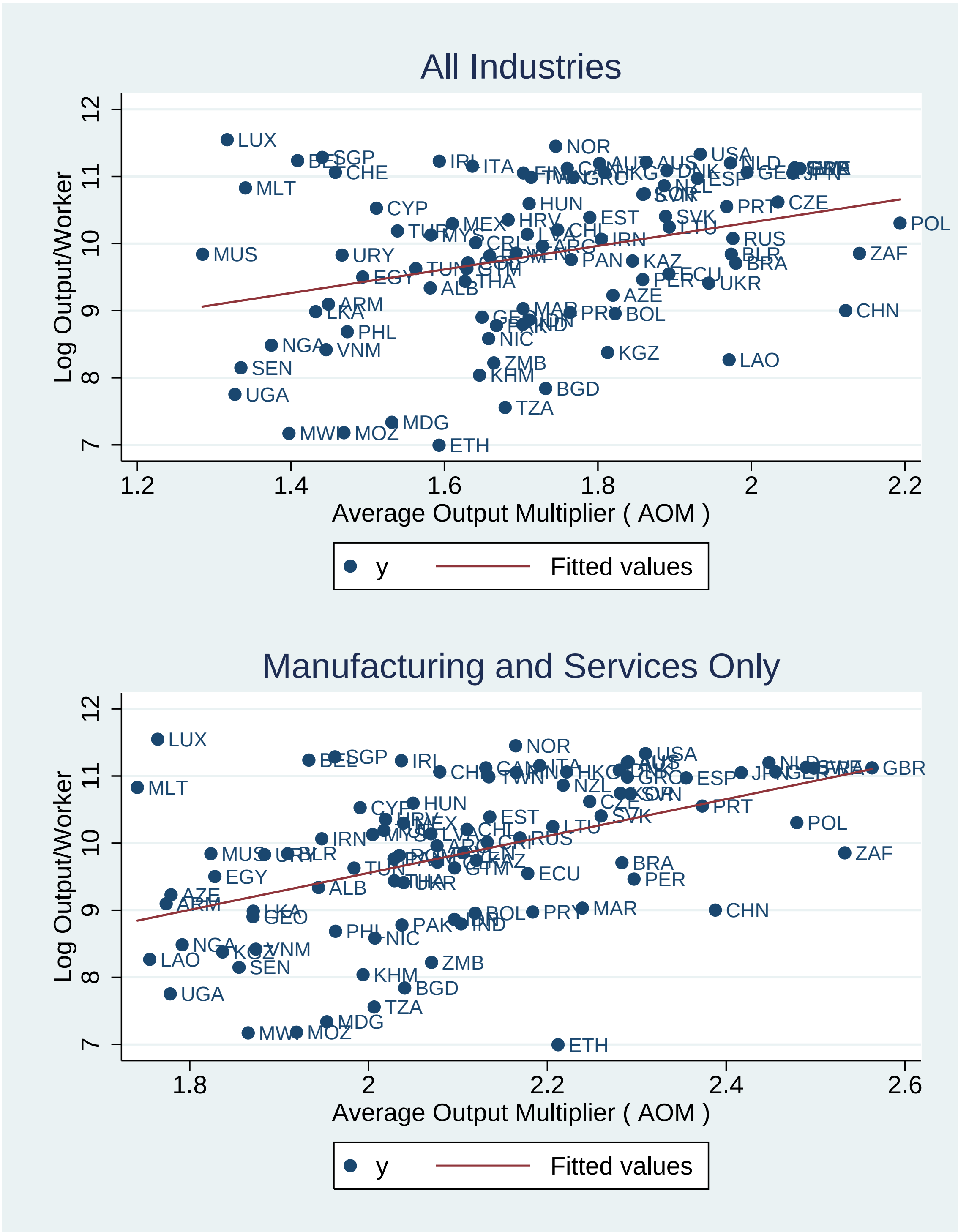
Figure 1: Correlations of Industry Coefficients with Aggregate Output per Worker



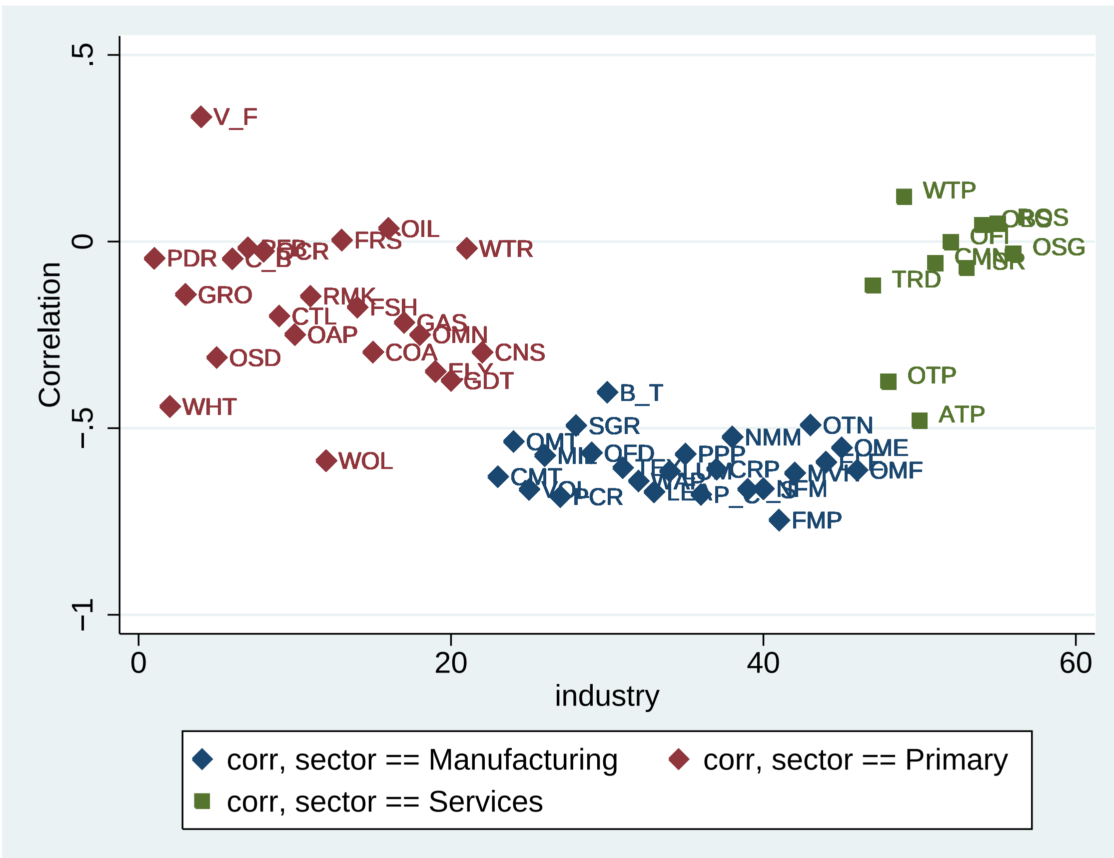
Notes Each dot represents the correlation between an individual industry linkage and aggregate log output per worker. Backward linkages calculated by averaging the entries of each column of the IO matrix **A**. Forward linkages calculated by averaging the elements of each row of the matrix **A**. Primary sector includes agriculture, mining, utilities and construction. Industry codes can be found in Appendix B. IO data are from GTAP7.

Figure 2: AOM and Output per Worker



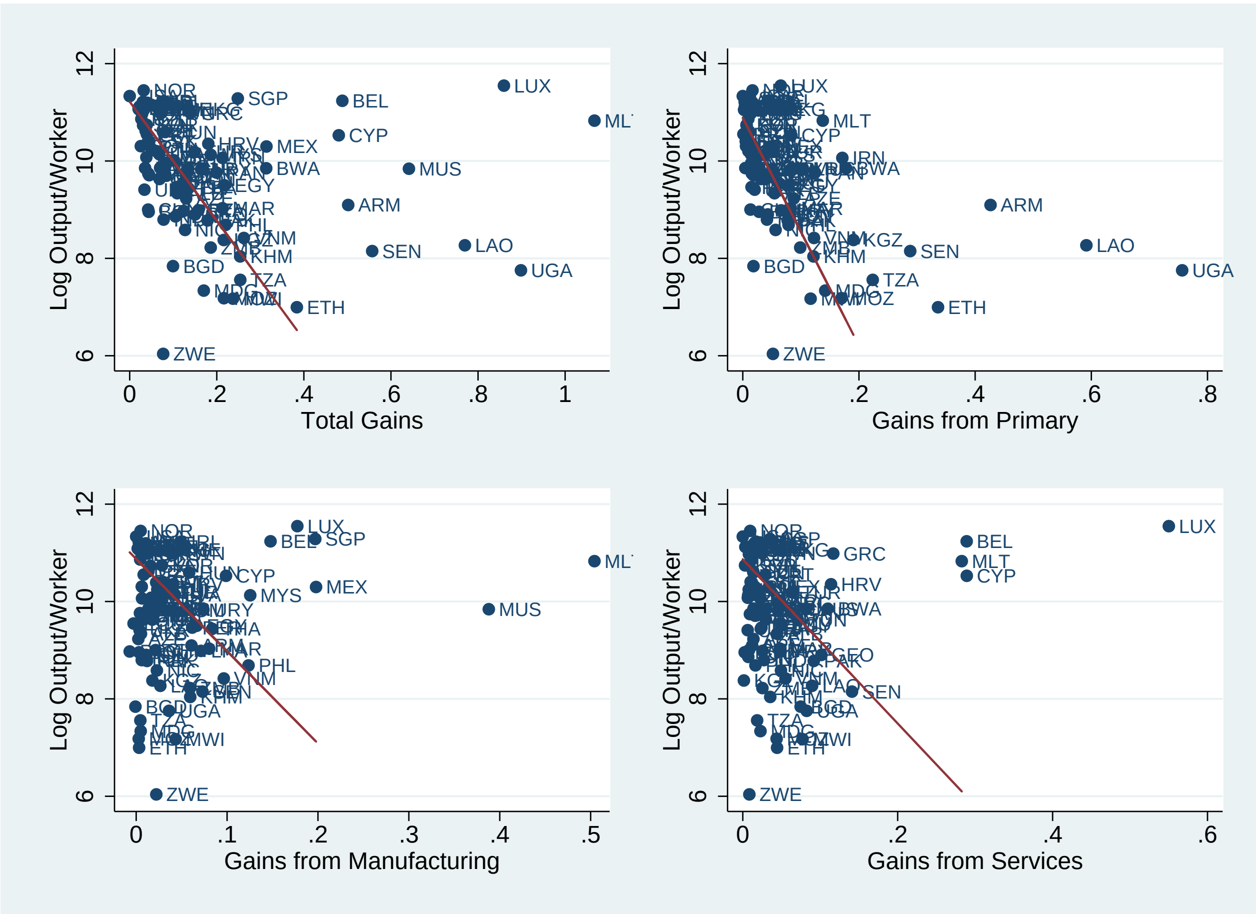
Notes AOM is calculated as $(\iota \mathbf{L} \iota)/N$ where $\mathbf{L}$ is the Leontief inverse of the input-output (IO) matrix $\mathbf{B}$, ι is the summer vector and N is the number of industries. AOM for manufacturing and services only is calculated by setting all entries of $\mathbf{B}$ associated with primary products to zero, then calculating AOM according to the formula above with N as the number of manufacturing and service industries. IO data are from GTAP7.

Figure 3: Correlation between Domestic and Imported Inputs



Notes Each dot represents the correlation between the domestic and imported intermediate shares for an industry. Primary sector includes agriculture, mining, utilities and construction. Industry codes can be found in Appendix B. IO data are from GTAP7.

Figure 4: Output per Worker and the Gains from Eliminating Distortions, US Technology Assumption



Notes Plots the gains from eliminating all distortions, then the gains from eliminating distortions in each broad sector holding all else constant. The gains from eliminating distortions are computed using the model outlined in 5.1 and Appendix A. The regression line is drawn using least median squares to ensure robustness against outliers. Primary sector includes agriculture, mining, utilities and construction. IO data are from GTAP7.

Figure 5: Output per Worker and the Gains from Eliminating Distortions, Adjusted Technology Assumption

Notes Plots the gains from eliminating all distortions, then the gains from eliminating distortions in each broad sector holding all else constant. The gains from eliminating distortions are computed using the model outlined in 5.1 and Appendix A. The Adjusted Technology assumption uses patterns in the 20 richest economies to predict technology for poor countries; see section 5.1. The regression line is drawn using least median squares to ensure robustness against outliers. Primary sector includes agriculture, mining, utilities and construction. IO data are from GTAP7.

Table 1: Panel: Observations by Region and Time Period

	Africa	Asia	Latin America	Eastern Europe & Transition	Western Europe & Offshoots
1950	0	0	2	0	0
1955	0	0	3	0	7
1960	0	1	4	0	4
1965	2	1	0	1	14
1970	5	7	5	0	15
1975	3	5	2	2	12
1980	1	3	1	0	6
1985	1	4	1	0	8
1990	1	4	0	0	10
1995	8	14	8	9	20
2000	15	17	14	18	19

Notes Eastern Europe and Transition includes the former Soviet republics of Armenia, Azerbaijan, Georgia, Kazakhstan and Kyrgyzstan, along with Turkey and Eastern Europe as conventionally defined. Western European "Offshoots" include Australia, Canada, Israel, New Zealand and the United States.

Table 2: IO coefficient means and correlations, GTAP7

Panel A: Means and standard deviations

		Using Sector		
		Primary Sector	Manufacturing	Services
Producing Sector	Primary Sector	0.11	0.14	0.04
		(0.06)	(0.11)	(0.04)
	Manufacturing	0.13	0.18	0.08
		(0.06)	(0.08)	(0.05)
	Services	0.12	0.16	0.20
		(0.05)	(0.09)	(0.07)

Panel B: Correlations with log output per worker

		Primary Sector	Manufacturing	Services
Prod. Sec.	Primary Sector	0.08	-0.55	-0.33
	Manufacturing	0.53	0.34	-0.13
	Services	0.38	0.06	0.46

Notes Primary sector is agriculture, mining, utilities and construction. Each country's IO table was aggregated into a 3x3, then each coefficient was averaged across countries to compute the means. Standard deviations in parentheses under the entries in panel A. Panel B reports the correlation coefficient of each aggregated IO entry with log output per worker.

Table 3: IO coefficient means and correlations, panel

Panel A: Means and standard deviations

		Using Sector		
		Primary Sector	Manufacturing	Services
Producing Sector	Primary Sector	0.11	0.14	0.04
		(0.06)	(0.08)	(0.03)
	Manufacturing	0.17	0.22	0.08
		(0.07)	(0.09)	(0.04)
	Services	0.16	0.12	0.17
		(0.06)	(0.06)	(0.07)

Panel B: Correlations with log output per worker

Prod. Sec.	Primary Sector	0.26	-0.58	-0.15
	Manufacturing	0.57	0.41	0.02
	Services	0.46	-0.09	0.31

Panel C: Correlations with log output per workers, country fixed effects

Prod. Sec.	Primary Sector	0.01	-0.56	-0.05
	Manufacturing	0.10	-0.27	-0.13
	Services	0.31	0.51	0.65

Notes Primary sector is agriculture, mining, utilities and construction. Each country's IO table was aggregated into a 3x3, then each coefficient was averaged across countries to compute the means. Standard deviations in parentheses under the entries in panel A. Panel B reports the correlation coefficient of each aggregated IO entry with log output per worker. Panel C reports the correlation between the residuals from regressing y and each IO coefficient separately on country dummies.

Table 4: Cross-section: Main Regression Results

	AOM						AOM-MS					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
AOM (AOM-MS)	1.69***	1.16***	0.92***	1.10***	1.32***	0.77***	2.70***	0.84**	0.85***	1.14***	1.16***	0.64**
	(0.61)	(0.31)	(0.28)	(0.29)	(0.27)	(0.24)	(0.55)	(0.33)	(0.32)	(0.33)	(0.31)	(0.29)
Rule of law		9.02***	7.89***	7.45***	6.78***	-2.78**		8.61***	7.15***	6.40***	6.34***	-3.31**
		(0.67)	(0.65)	(0.62)	(1.07)	(1.38)		(0.77)	(0.77)	(0.76)	(1.26)	(1.47)
Dist. Equator			0.14***	0.14***	0.17***	0.16***			0.18***	0.18***	0.18***	0.17***
			(0.04)	(0.04)	(0.06)	(0.05)			(0.04)	(0.04)	(0.06)	(0.05)
Openness				0.22***	0.24***	0.30***				0.24***	0.22***	0.29***
				(0.07)	(0.08)	(0.07)				(0.06)	(0.07)	(0.06)
Central Planning					-1.94	-2.24					-0.22	-1.25
					(2.11)	(1.87)					(2.29)	(1.89)
Govt. Consumption					-4.99**	-2.57*					-4.33**	-2.11
					(1.98)	(1.39)					(2.00)	(1.42)
Tech. Adoption						4.84***						5.03***
						(0.68)						(0.72)
Observations	89	89	89	89	89	76	89	89	89	89	89	76
R-squared	0.09	0.69	0.72	0.73	0.75	0.85	0.21	0.66	0.71	0.72	0.74	0.85

Notes Dependent variable is $\log(RGDPWOK)$ from the PWT 7.0 in all specifications. Robust standard errors in parentheses. Rule of Law the average value over 1996-2008 of the Rule of Law index from Kaufmann et al. (2009). Openness is $(Imports + Exports)/GDP$ from the PWT. Central Planning is a dummy variable that takes the value of 1 if a country has a history of central planning. Government Consumption is from the PWT. Tech Adoption is the index of technology adoption constructed by Comin et al. (2008). ***, **, * denote statistical significance at 1%, 5% and 10%.

Table 5: Cross-section: Components of Output per Worker

Dependent variable	AOM		AOM-MS		Number of Obs.
	β	R^2	β	R^2	
	(1)	(2)	(3)	(4)	(5)
$\frac{\alpha}{1-\alpha}\log\left(\frac{K}{Y}\right)$	0.08	0.20	0.16*	0.22	74
	(0.09)		(0.09)		
$\log(h)$	0.19**	0.72	0.14	0.71	73
	(0.09)		(0.09)		
$\log(TFP)$	0.45**	0.82	0.48**	0.82	71
	(0.20)		(0.22)		

Notes Each row reports the results of using either all industries (AOM) or manufacturing and service industries only ($AOM - MS$) in otherwise identical regressions. Dependent variable is shown in the left column. Robust standard errors in parentheses. ***, **, * denote statistical significance at 1%, 5% and 10%. Controls include all controls used in column 6 of Table 4.

Table 6: Panel: Main Regression Results

	AOM				AOM-MS			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AOM(MS)	1.96***	1.15**	0.94***	0.30**	2.46***	2.28***	1.28***	0.68***
	(0.40)	(0.38)	(0.25)	(0.10)	(0.18)	(0.45)	(0.35)	(0.18)
Polity IV			1.15**	0.38			1.05**	0.39
			(0.41)	(0.30)			(0.42)	(0.27)
Openness			0.93***	0.51***			0.81***	0.51***
			(0.13)	(0.05)			(0.13)	(0.05)
Govt. Cons.			-5.56***	-5.24***			-5.21***	-5.27***
			(0.70)	(0.93)			(0.70)	(0.80)
R-squared	0.13	0.10	0.65	0.78	0.12	0.27	0.66	0.79
Obs.	277	240	233	233	277	240	233	233
Groups	99	62	59	59	99	62	59	59
Country FE	N	Y	Y	Y	N	Y	Y	Y
Decade Dum.	N	N	N	Y	N	N	N	Y

Notes Columns 1-4 report results using AOM, while columns 5 - 8 report results using $AOM - MS$ from otherwise identical regressions. Dependent variable is log RGDPWOK from the PWT 7.0 in all specifications. Driscoll-Kraay (1998) standard errors in parentheses. ***, **, * denote statistical significance at 1%, 5% and 10%. For specifications with fixed effects, we report the within R^2.

Table 7: Robustness Checks

Row	Specification	Cross-section AOM	Cross-section AOM-MS	Cross-section Obs.	Panel AOM	Panel AOM-MS	Panel Obs.
1	WAOM	0.48*	0.35*	76	0.25***	0.39***	233
		(0.26)	(0.19)		(0.08)	(0.14)	
2	Imported inputs	0.62*	0.36	76			
		(0.33)	(0.43)				
3	Drop older				0.24	0.53***	211
	observations				(0.13)	(0.17)	
4	Drop very	0.58***	0.59***	70	0.29**	0.72***	214
	poor countries	(0.22)	(0.22)		(0.10)	(0.20)	
5	Include only	-0.17	-0.11	25	-0.01	0.26*	128
	rich countries	(0.10)	(0.16)		(0.06)	(0.14)	
6	Drop small AOM	0.81**	0.73*	71	0.40***	0.79***	207
		(0.31)	(0.38)		(0.12)	(0.19)	
7	Drop very	0.77***	0.69**	60	0.37**	0.76***	213
	open countries	(0.27)	(0.34)		(0.12)	(0.21)	
8	Drop small	0.77***	0.69**	70	0.34***	0.66***	207
	countries	(0.25)	(0.31)		(0.08)	(0.15)	
9	Median regression	0.83***	0.74**	76	0.30	0.31	233
		(0.31)	(0.33)		(0.22)	(0.29)	
10	Huber robust	0.65**	0.70**	76	0.12	0.40**	233
	regression	(0.28)	(0.31)		(0.14)	(0.18)	

Notes Each row reports the results of using either all industries (AOM) or manufacturing and service industries only ($AOM - MS$) to calculate the average output multiplier in the panel and cross sectional specifications. Dependent variable is $\log(RGDPWOK)$ from the PWT 7.0 in all specifications. Robust standard errors in parentheses. All regressions include the controls used in column 6 of table 4, or column 4 of table 6 . Row 1 replaces AOM with $WAOM$. Row 2 includes the share of imported inputs in total output as a regressor. Row 3 drops observations before 1970. Row 4 drops countries with output per worker less than \$3,000. Row 5 drops countries with output per worker less than \$36,000 (\$$22,000$ in the panel). Row 6 drops countries with $AOM < 1.4$ or $AOM - MS < 1.9$, respectively ($AOM < 1.45$ or $AOM - MS < 2.28$ in the panel). Row 7 drops countries with $(imports + exports)/rgdp > 1.1$. Row 8 drops countries with population less that 4 million. Row 9 reports the LAD estimate of κ with bootstrapped standard errors (1000 replications). Row 10 reports the results for Huber robust regression. ***, **, * denote statistical significance at 1%, 5% and 10%.

Table 8: Distortions and Gains, GTAP7 Summary

	Avg. Distortion		Gains	
	US Tech	Adj. Tech	US Tech	Adj. Tech
Mean	0.16	0.04	0.17	0.10
Median	0.16	0.06	0.10	0.06
75th pctile	0.26	0.20	0.21	0.13
90th pctile	0.40	0.32	0.38	0.21
St. Dev.	0.17	0.20	0.20	0.08
Correlation	0.75		0.39	
Observations	91	71	91	71

Notes Distortions are computed for each industry and averaged across industries for each country using the methods outlined in section 5.1. The Adjusted Technology assumption uses patterns in the 20 richest economies to predict technology for poor countries; see section 5.1. Statistics are based on the cross-country distribution of these average distortions. The gains from eliminating distortions are computed using the model outlined in 5.1 and Appendix A. All data from GTAP7.

Table 9: Distortions and Gains, Panel Summary

	Avg. Distortion	Total Gains	Prim. Gains	Mnfg. Gains	Serv. Gains
Mean	0.08	0.08	0.06	0.01	0.00
Median	0.09	0.03	0.01	0.00	0.00
75th pctile	0.21	0.07	0.05	0.01	0.02
90th pctile	0.29	0.22	0.15	0.02	0.05
St. Dev.	0.20	0.14	0.13	0.02	0.05
Time Trend	-0.02	-0.02	-0.02	0.00	0.00

Notes Distortions are computed for each industry and averaged across industries for each country using the methods outlined in section 5.1. Statistics are based on the cross-country distribution of these average distortions. We use patterns in the 20 richest economies to predict technology for poor countries; see section 5.1. The gains from eliminating distortions are computed using the model outlined in 5.1 and Appendix A. The sectoral gains are computed by eliminating distortions in that sector only, holding all else constant. The IO matrix and value added shares come from the original IO tables detailed in Table 12 in Appendix B. Capital value added shares are assumed constant over time and come from GTAP7. The time trend coefficient comes from a regression of the gains on country fixed effects and a time trend.

Table 10: Model and Data Comparisons

	GTAP7 Sample	
	US Tech	Adj. Tech
Panel A: $\log(\epsilon_{ct}) = const + \kappa AOM_{ct} + error_{ct}$		
κ	0.46***	0.14***
	(0.08)	(0.03)
Obs.	89	69
Panel B: $\log(TFP_{ct}) = \kappa \log(\epsilon_{ct}) + \rho \mathbf{X}_{ct} + error_{ct}$		
κ	0.47	0.93
	(0.36)	(1.06)
Obs.	71	52
Panel C: $y_{ct} = \kappa \log(\epsilon_{ct}) + \rho \mathbf{X}_{ct} + error_{ct}$		
κ	1.17***	1.94
	(0.43)	(1.37)
Obs.	76	57

Notes: $\mathbf{X}_c$ includes a constant and all regressors from column 6 of Table 4 (Rule of Law, Distance from Equator, Openness, Central Planning, Government Consumption, and Technology Adoption). ϵ_{ct} is the size of distortions to TFP implied by the model (see equation 5). Robust standard errors in parentheses. ***, **, * denote statistical significance at 1%, 5% and 10%.

7 Appendices: Not for publication

A Derivations

A.1 One-Sector Growth Model with Intermediate Goods

This section presents a one sector Ramsey model with intermediate products. Gross output is given by

$$Y(t) = \left(K(t)^{\alpha} L(t)^{1-\alpha}\right)^{1-\sigma} X(t)^{\sigma} \tag{10}$$

where X is the amount of intermediate goods used in production. At any point in time competitive firms solve

$$\max_{K(t),L(t),X(t)} (1-\tau_Y)(K(t)^{\alpha}(A(t)L(t))^{1-\alpha})^{1-\sigma} X(t)^{\sigma} - w(t)L(t) - r(t))K(t) - (1+\tau_X)X(t) \tag{11}$$

where τ_Y is a distortion that acts as a sales tax and τ_X is a distortion that acts as a tax on intermediate purchases. Firm optimization implies that, at any point in time, gross output is given by

$$Y(t) = K(t)^{\alpha} L(t)^{1-\alpha} \left[A^{1-\alpha} \left(\frac{\sigma}{\tau}\right)^{\frac{\sigma}{1-\sigma}}\right] \tag{12}$$

and net output or GDP is

$$Y(t) - X(t) = Y(t)\left(1 - \frac{\sigma}{\tau}\right) = K(t)^{\alpha} L(t)^{1-\alpha} \left[A^{1-\alpha} \left(\frac{\sigma}{\tau}\right)^{\frac{\sigma}{1-\sigma}} \left(1 - \frac{\sigma}{\tau}\right)\right] \tag{13}$$

where $\tau = \frac{1+\tau_X}{1-\tau_Y}$ is the "net tax rate" and the term in brackets equals the Solow residual or measured TFP. Note that, given fixed capital and labor stocks, there is no distinction between the effects of sales taxes and taxes on intermediates.

We now establish the comparative statics of TFP at any point in time with respect to τ. Let

$$G = A^{1-\alpha} \left(\frac{\sigma}{\tau}\right)^{\frac{\sigma}{1-\sigma}}$$

We can then derive

$$\frac{\partial TFP}{\partial \tau} = G\left[\frac{\sigma(1-\tau)}{\tau^2(1-\sigma)}\right] \begin{cases} < 0 & \text{if } \tau > 1 \\ = 0 & \text{if } \tau = 1 \\ > 0 & \text{if } \tau < 1 \end{cases} \tag{14}$$

$$\frac{\partial^2 TFP}{\partial\sigma\partial\tau} = G\frac{1-\tau}{\tau^4(1-\sigma)^2}\left[\tau^2 - \sigma(1-\sigma)(1-\tau) + \sigma(\tau-\sigma)\log(\sigma/\tau)\right] \tag{15}$$

$$\begin{cases} < 0 & \text{if } \tau > 1 \\ = 0 & \text{if } \tau = 1 \\ > 0 & \text{if } \tau < 1 \end{cases}$$

Higher taxes on intermediates, direct (τ_X) or indirect (τ_X), reduce intermediate usage from its optimal level and lower measured TFP. A higher intermediate share implies that intermediates are relatively more important in the production process, so distortions to intermediate inputs (i.e. deviations from $\tau = 1$) are more costly.

We add a household sector in order to study how intermediate goods and distortions affect the steady state level of capital stock. Suppose a representative consumer solves

$$\max_{c(t)} \int_{t=0}^{\infty} e^{-\rho t}\frac{C(t)^{1-\theta}}{1-\theta}\,dt \tag{16}$$

$$s.t.\ \ \dot{a}(t) = [r(t)-\delta]\,a(t) + w(t) + \tau_Y y(t) + \tau_X x(t) - c(t) \tag{17}$$

where lowercase variables are per capita values and δ is the capital depreciation rate. Technology A grows at a constant exogenous rate g.

Letting $k = K/AL$, $\tilde{c} = c/A$ and $x = X/AL$ we can express the two dynamic equations of the model as

$$\frac{\dot{\tilde{c}}}{\tilde{c}} = \frac{r(t)-\rho-\delta}{\theta} - g \tag{18}$$

$$\dot{k} = k^{\alpha}\,(\sigma/\tau)^{\frac{\sigma}{1-\sigma}}\,[(1-\tau_Y)(1-\sigma) + \tau_Y + \tau_X\sigma/\tau] - \tilde{c} - (g+\delta)k \tag{19}$$

where $r(t) = (1-\tau_Y)(1-\sigma)\alpha k^{\alpha-1}(\sigma/\tau)^{\frac{\sigma}{1-\sigma}}$. Solving for the steady state value of capital per effective labor, we find

$$\bar{k} = \left[\frac{\theta g + \rho + \delta}{\alpha(1-\tau_Y)(1-\sigma)}\,(\sigma/\tau)^{-\frac{\sigma}{1-\sigma}}\right]^{\frac{1}{\alpha-1}} \tag{20}$$

Along the balanced growth path, net output per worker is given by

$$\begin{aligned}\bar{va} &= A\bar{k}^{\alpha} \cdot \left(\frac{\sigma}{\tau}\right)^{\frac{\sigma}{1-\sigma}} \left(\frac{\tau-\sigma}{\tau}\right) \\ &= A\left[\frac{\theta g+\rho+\delta}{\alpha(1-\tau_Y)(1-\sigma)}(\sigma/\tau)^{-\frac{\sigma}{1-\sigma}}\right]^{\frac{1}{\alpha-1}} \cdot \left(\frac{\sigma}{\tau}\right)^{\frac{\sigma}{1-\sigma}} \left(\frac{\tau-\sigma}{\tau}\right) \end{aligned} \tag{21}$$

Both taxes reduce capital accumulation, but τ_Y has a larger negative effect because it directly reduces the rate of return on capital as well as indirectly through its effect on TFP. The effect of net subsidies ($\tau < 1$) on output per worker on the balanced growth path is ambiguous because subsidies reduce TFP but encourage capital accumulation to a varying degree depending on the specific mix of distortions.

We can establish the following:

$$\frac{\partial \log(\bar{k})}{\partial \tau_Y} = \frac{1}{(\alpha-1)(1-\tau_Y)(1-\sigma)} < 0 \tag{22}$$

$$\frac{\partial \log(\bar{k})}{\partial \tau_X} = \frac{\sigma}{(\alpha-1)(1+\tau_X)(1-\sigma)} < 0 \tag{23}$$

The last two effects are straightforward: taxing sales and intermediates reduces the steady state capital stock. Subsidies, on the other hand, encourage excessive capital accumulation.

A.2 Comparative Statics of σ

The comparative statics of output and productivity with respect to the factor shares in a Cobb-Douglas production function depends crucially on whether technology augments labor/capital, or intermediate goods/ is neutral. For example, consider the functions

$$F_1 = A(K^{\alpha}L^{\beta})^{1-\sigma}X^{\sigma} \tag{24}$$

$$F_2 = (K^{\alpha}(AL)^{1-\alpha})^{1-\sigma}X^{\sigma} \tag{25}$$

and define let TFP_1 and TFP_2 denote total factor productivity in the value-added form of the production function (assuming no distortions),

$$TFP_1 = (1-\sigma)\sigma^{\frac{\sigma}{1-\sigma}}A^{\frac{1}{1-\sigma}} \tag{26}$$

$$TFP_2 = (1-\sigma)\sigma^{\frac{\sigma}{1-\sigma}} A^{1-\alpha} \tag{27}$$

It is easy to show that $d/d\sigma \ (1-\sigma)\sigma^{\frac{\sigma}{1-\sigma}} < 0$, which implies that $dTFP_2/d\sigma < 0$. But when σ enters into the exponent of A as in TFP_1 the magnitude of A determines the sign of the derivative. For A large enough $dTFP_1/d\sigma > 0$ and for A small enough we get the opposite. These features make conducting comparative statics with σ very unappealing since there is no good reason to prefer one specification to another. Moreover the magnitude of A depends on the units in which inputs and outputs are measured, which in the case of TFP_1 will affect the magnitude and sign of the elasticity of TFP with respect to σ.

A.3 CES Generalization

Consider the CES generalization of the gross output production function (10),[29]

$$Y = (a_L(\pi_L L)^\rho + a_K(\pi_K K)^\rho + a_X(\pi_X X)^\rho)^{\frac{1}{\rho}} \tag{28}$$

Following the same steps as in the previous sections, in a competitive economy with distortions the intermediate goods share will be

$$\frac{X}{Y} = \left(\frac{a_X \pi_X^\rho}{t}\right)^{\frac{1}{1-\rho}} \tag{29}$$

and net output will be

$$Y - X = constant \cdot \frac{1 - a_X \pi_X^{\frac{\rho}{1-\rho}} t^{\frac{-1}{1\rho}}}{\left(1 - a_X \pi_X^{\frac{\rho}{1-\rho}} t^{\frac{-\rho}{1\rho}}\right)^{\frac{1}{\rho}}} \tag{30}$$

This expression need not be positive (or real) for all admissible values of t and ρ. Intuitively, if the tax t is high and ρ is low the firm must pay more for its intermediate input than it can get for its output, so production shuts down and the formula ceases to be meaningful. If t is low and ρ is high enough the firm can make infinite profits by simply using intermediate goods to produce final goods without the use of capital and labor at all, which also cannot be an equilibrium. Therefore, we confine our discussion to the parameter space for which equation (30) delivers an economically sensible answer.

We are interested in how the impact of distortions on aggregate output varies with the elas-

[29]This is a "normalized" CES function, appropriate for doing comparative statics on the elasticity of substitution (Klump et al., 2012).

ticity of substitution. Intuitively, there are two off-setting effects. When the elasticity of substitution is lower, a given tax causes a relatively smaller change in the input-output coefficient (29). On the other hand, the misallocation in input quantities induced by the distortion is more costly the lower the elasticity of substitution. Which effect dominates depends non-monotonically on the elasticity. Figure 6 shows the impact of different taxes for several values of the elasticity of substitution. For an elasticity of substitution of 1/2 (i.e. $\rho = -1$)), the output cost of a given level of distortion is much larger than in the case of a unit elasticity. The output cost is still larger than in the unit elasticity case when elasticity of $1/11$, but the difference is much smaller. In the Leontief limit, the output cost of distortions is zero.

A.4 Multi-Sector Model

In our simulations we use the closed economy version of the multisector neoclassical growth model with distortions explored by Jones (2011b) with 56 sectors. We refer the reader to that paper for an in depth discussion. In this appendix we simply specify the model formally for easy reference.

The production side of the economy consists of multiple intermediate goods sectors and a final goods sector. Each intermediate sector has competitive input and output markets. Production in sector i takes place using the Cobb-Douglas technology

$$Y_i = \left(K_i^{\alpha_i}\left(A_i L_i\right)^{1-\alpha_i}\right)^{1-\sigma_i} \cdot \prod_{j=1}^{n} X_{ij}^{\sigma_{ij}} \tag{31}$$

where the X_{ij} are the intermediate goods from sector j used by sector i and $\sigma_i = \sum_{j=1}^{n} \sigma_{ij}$, K is capital, L is labor, and A is the labor augmenting technology level. Firms choose input and output levels to maximize profits:

$$\max_{K_i, L_i, X_{ij}} \; (1-\tau_i^Y) P_i Y_i - w L_i - r K_i - \sum_{j=1}^{n} P_j X_{ij} \tag{32}$$

where a fraction τ_i^Y of the firm's output is stolen and rebated lump sum to consumers. The firm's output is sold either to other intermediate goods producers or to the final goods sector, whose Cobb-Douglas production function is

$$Y = \prod_i c_i^{\gamma_i} \tag{33}$$

where $\sum_i \gamma_i = 1$. Consumers then purchase this composite final good. Consumers own all factors of production (which are in fixed supply) and care only about consumption, and since the model is static the solution to their optimization problem is to simply spend all their income on this consumption good.

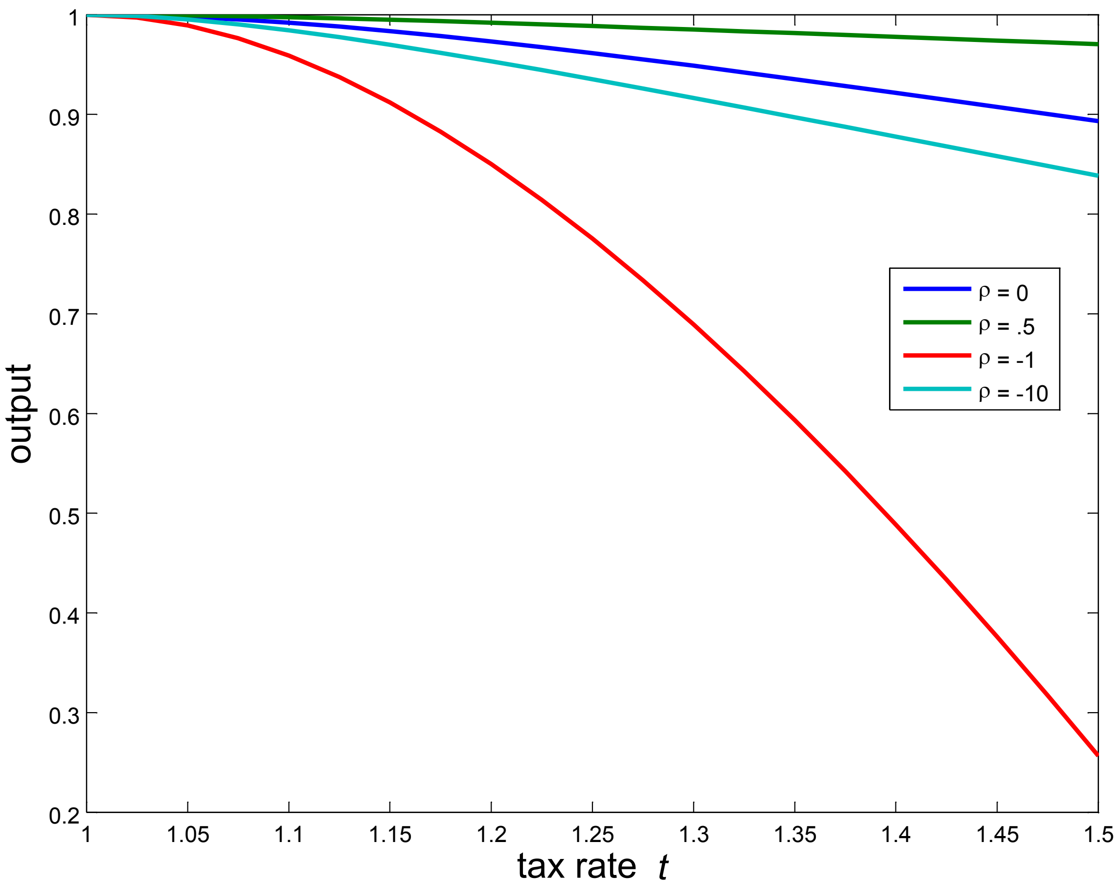
Market clearing requires that all intermediate production is uses to produce either other intermediates or final goods,

$$Y_i = c_i + \sum_j X_{ij} \tag{34}$$

all final good production is consumed,

$$Y = C \tag{35}$$

Figure 6: Output cost of distortions for CES production functions



and all factors of production are fully employed

$$\sum_i K_i = K \tag{36}$$

$$\sum_i L_i = L \tag{37}$$

A competitive equilibrium is a set of quantities $C, Y, Y_i, K_i, L_i, X_{ij}$ and prices P_i, r, w such that all firms are maximizing profits, all markets clear and consumers consume optimally.

Jones (2011b) shows that in this competitive equilibrium aggregate output is a Cobb-Douglas function of aggregate capital, labor and TFP, where TFP is the product of a term that involves no distortions and a term that does, ϵ. In our simulations we focus on variation in ϵ, so we provide the formula below.

$$\log(\epsilon) = \omega + \mu' \bar{\eta} \tag{38}$$

where

$$
\begin{aligned}
\omega &= \gamma'\omega_c + \mu'\omega_q \\
\mu' &= \gamma'(I - \mathbf{B}^*) \\
\bar{\eta}_i &= \log\left(A_i(1-\tau_i)\right) \\
\omega_q &= \omega_K + \omega_L + \omega_X \\
\omega_{ci} &= \log\left(\frac{\gamma_i}{\beta_i}\right) \\
\beta &= (I - \mathbf{B}')^{-1}\gamma \\
\omega_{Xi} &= \sum_{j=1}^{N} \sigma_{ij}\log(\sigma_{ij}\beta_i/\beta_j) \\
\omega_{Ki} &= \delta_{Ki}\log(\theta_{Ki}) \\
\omega_{Li} &= \delta_{Li}\log(\theta_{Li}) \\
\theta_{Ki} &= \frac{\delta_{Ki}\beta_i}{\sum_{j=1}^{N}(1-\tau_j)\delta_{Kj}\beta_j} \\
\theta_{Li} &= \frac{\delta_{Li}\beta_i}{\sum_{j=1}^{N}(1-\tau_j)\delta_{Lj}\beta_j} \\
\delta_{Ki} &= \alpha_i(1-\sigma_i) \\
\delta_{Li} &= (1-\alpha_i)(1-\sigma_i)
\end{aligned}
$$

B Data Appendix

Table 11: Cross Section Sample of Countries

countrycode	country	y	AOM	AOM-MS
ALB	Albania	9.34	1.58	1.94
ARG	Argentina	9.96	1.73	2.08
ARM	Armenia	9.10	1.45	1.77
AUS	Australia	11.21	1.86	2.29
AUT	Austria	11.19	1.80	2.29
AZE	Azerbaijan	9.23	1.82	1.78
BEL	Belgium	11.24	1.41	1.93
BGD	Bangladesh	7.84	1.73	2.04
BLR	Belarus	9.84	1.97	1.91
BOL	Bolivia	8.96	1.82	2.12
BRA	Brazil	9.71	1.98	2.28
CAN	Canada	11.12	1.76	2.13
CHE	Switzerland	11.06	1.46	2.08
CHL	Chile	10.20	1.75	2.11
CHN	China	9.00	2.12	2.39
COL	Colombia	9.72	1.63	2.08
CRI	Costa Rica	10.01	1.64	2.13
CYP	Cyprus	10.53	1.51	1.99
CZE	Czech Republic	10.62	2.03	2.25
DNK	Denmark	11.09	1.89	2.28
ECU	Ecuador	9.55	1.89	2.18
EGY	Egypt	9.50	1.49	1.83
ESP	Spain	10.97	1.93	2.36
EST	Estonia	10.39	1.79	2.14
ETH	Ethiopia	7.00	1.59	2.21
FIN	Finland	11.05	1.70	2.17
FRA	France	11.12	2.06	2.50
GBR	United Kingdom	11.12	2.06	2.56
GEO	Georgia	8.90	1.65	1.87
GER	Germany	11.06	1.99	2.46
GRC	Greece	10.98	1.77	2.29

GTM	Guatemala	9.63	1.63	2.10
HKG	Hong Kong	11.06	1.81	2.22
HRV	Croatia	10.35	1.68	2.02
HUN	Hungary	10.59	1.71	2.05
IDN	Indonesia	8.86	1.71	2.10
IND	India	8.80	1.70	2.10
IRL	Ireland	11.23	1.59	2.04
IRN	Iran	10.06	1.80	1.95
ITA	Italy	11.15	1.64	2.19
JPN	Japan	11.05	2.05	2.42
KAZ	Kazakhstan	9.74	1.85	2.12
KGZ	Kyrgyzstan	8.38	1.81	1.84
KHM	Cambodia	8.04	1.65	1.99
KOR	Korea, Republic of	10.74	1.86	2.28
LAO	Laos	8.27	1.97	1.76
LKA	Sri Lanka	8.99	1.43	1.87
LTU	Lithuania	10.25	1.89	2.21
LUX	Luxembourg	11.55	1.32	1.76
LVA	Latvia	10.14	1.71	2.07
MAR	Morocco	9.03	1.70	2.24
MDG	Madagascar	7.34	1.53	1.95
MEX	Mexico	10.30	1.61	2.04
MLT	Malta	10.83	1.34	1.74
MOZ	Mozambique	7.18	1.47	1.92
MUS	Mauritius	9.84	1.28	1.82
MWI	Malawi	7.17	1.40	1.87
MYS	Malaysia	10.13	1.58	2.00
NIC	Nicaragua	8.58	1.66	2.01
NLD	Netherlands	11.20	1.97	2.45
NOR	Norway	11.45	1.75	2.16
NZL	New Zealand	10.86	1.89	2.22
PAK	Pakistan	8.78	1.67	2.04
PAN	Panama	9.76	1.77	2.03
PER	Peru	9.46	1.86	2.30

PHL	Philippines	8.69	1.47	1.96
POL	Poland	10.30	2.19	2.48
PRT	Portugal	10.55	1.97	2.37
PRY	Paraguay	8.97	1.76	2.18
ROM	Romania	9.82	1.66	2.03
RUS	Russia	10.08	1.98	2.17
SEN	Senegal	8.15	1.33	1.86
SGP	Singapore	11.28	1.44	1.96
SVK	Slovak Republic	10.40	1.89	2.26
SVN	Slovenia	10.73	1.86	2.29
SWE	Sweden	11.13	2.06	2.49
THA	Thailand	9.44	1.63	2.03
TUN	Tunisia	9.63	1.56	1.98
TUR	Turkey	10.19	1.54	2.02
TWN	Taiwan	10.99	1.71	2.13
TZA	Tanzania	7.56	1.68	2.01
UGA	Uganda	7.75	1.33	1.78
UKR	Ukraine	9.41	1.94	2.04
URY	Uruguay	9.83	1.47	1.88
USA	United States	11.33	1.93	2.31
VEN	Venezuela	9.86	1.69	2.11
VNM	Vietnam	8.42	1.45	1.87
ZAF	South Africa	9.85	2.14	2.53
ZMB	Zambia	8.22	1.66	2.07

Sources: Penn World Tables 7.0, GTAP7 at https://www.gtap.agecon.purdue.edu

Table 12: Non-GTAP7 Countries and Sources

Country	years	Source	In Sample?
Argentina	1950, 1953, 1959, 1963, 1970	United Nations Economic Commission for Latin America, Tablas de insumo-producto en America Latina, Santiago de Chile : Naciones Unidas, 1983	Yes
Argentina	1997	OECD, GTAP5	Yes
Australia	1968, 1974, 1986, 1989, 1994, 1998, 2004	OECD, GTAP5	Yes
Austria	1961, 1964, 1976	Economic Commission for Europe, Standardized input-output tables of ECE countries ..., New York, United Nations, various years	Yes
Austria	1995, 1997, 2000, 2004	OECD, GTAP5	Yes
Burundi	1970	UNIDO, Input-output tables for developing countries, New York : United Nations, 1985	Yes
Belgium	1959, 1965, 1970	Economic Commission for Europe, Standardized input-output tables of ECE countries ..., New York, United Nations, various years	Yes
Belgium	1995, 2000, 2004	OECD, GTAP5	Yes
Bangladesh	1962	UNIDO, Input-output tables for developing countries, New York : United Nations, 1985	Yes
Bangladesh	1997	GTAP5	Yes
Bulgaria	1963	Economic Commission for Europe, Standardized input-output tables of ECE countries for years around 1959, New York, United Nations, 1972	Yes
Bolivia	1958	United Nations Economic Commission for Latin America, Tablas de insumo-producto en America Latina, Santiago de Chile : Naciones Unidas, 1983	Yes
Botswanna	1997	GTAP5	Yes

Brazil	1959	United Nations Economic Commission for Latin America, Tablas de insumo-producto en America Latina, Santiago de Chile : Naciones Unidas, 1983	No, no domestic gross output
Brazil	1970	United Nations Economic Commission for Latin America, Tablas de insumo-producto en America Latina, Santiago de Chile : Naciones Unidas, 1983	Yes
Brazil	1995, 1996, 1997, 2000, 2005	OECD, GTAP5	Yes
Canada	1965, 1971, 1975	Economic Commission for Europe, Standardized input-output tables of ECE countries ..., New York, United Nations, various years	Yes
Canada	1976, 1981, 1986, 1990, 1995, 1997, 2000	OECD, GTAP5	Yes
Switzerland	2001	OECD, GTAP5	Yes
Chile	1962	United Nations Economic Commission for Latin America, Tablas de insumo-producto en America Latina, Santiago de Chile : Naciones Unidas, 1983	Yes
Chile	1977	UNIDO, Input-output tables for developing countries, New York : United Nations, 1985	Yes
Chile	1986, 1996, 1997	http://www.bcentral.cl, GTAP5	Yes
China	1995, 1997, 2000, 2002	OECD, GTAP5	Yes
Ivory Coast	1976	UNIDO, Input-output tables for developing countries, New York : United Nations, 1985	No, trade margins excluded
Ivory Coast	1981	UNIDO, Input-output tables for developing countries, New York : United Nations, 1985	No, major errors
Congo	1967	UNIDO, Input-output tables for developing countries, New York : United Nations, 1985	No, trade margins excluded
Columbia	1953	United Nations Economic Commission for Latin America, Tablas de insumo-producto en America Latina, Santiago de Chile : Naciones Unidas, 1983	No, missing service sectors

Columbia	1956	United Nations Economic Commission for Latin America, Tablas de insumo-producto en America Latina, Santiago de Chile : Naciones Unidas, 1983	Yes
Columbia	1960	United Nations Economic Commission for Latin America, Tablas de insumo-producto en America Latina, Santiago de Chile : Naciones Unidas, 1983	No, missing service sectors
Columbia	1970	United Nations Economic Commission for Latin America, Tablas de insumo-producto en America Latina, Santiago de Chile : Naciones Unidas, 1983	No, trade and transport margins excluded
Columbia	1997	GTAP5	Yes
Costa Rica	1957	United Nations Economic Commission for Latin America, Tablas de insumo-producto en America Latina, Santiago de Chile : Naciones Unidas, 1983	No, missing service sectors
Costa Rica	1972	United Nations Economic Commission for Latin America, Tablas de insumo-producto en America Latina, Santiago de Chile : Naciones Unidas, 1983	No, missing mining sectors
Czechoslovakia	1962, 1967, 1973, 1977	Economic Commission for Europe, Standardized input-output tables of ECE countries ..., New York, United Nations, various years	Yes
Czech Republic	1995, 2000, 2005	OECD	Yes
Denmark	1966-2005, annual	http://www.dst.dk, GTAP5	Yes
Dominican Republic	1962	United Nations Economic Commission for Latin America, Tablas de insumo-producto en America Latina, Santiago de Chile : Naciones Unidas, 1983	No, missing service sectors
Ecuador	1972, 1975	United Nations Economic Commission for Latin America, Tablas de insumo-producto en America Latina, Santiago de Chile : Naciones Unidas, 1983	No, trade margins excluded
Egypt	1973	UNIDO, Input-output tables for developing countries, New York : United Nations, 1985	No, trade margins excluded
Spain	1966, 1975	Economic Commission for Europe, Standardized input-output tables of ECE countries ..., New York, United Nations, various years	Yes

Spain	1995, 1997, 2000, 2004, 2005	OECD, GTAP5. Eurostat	Yes
Estonia	1997, 2000, 2005	OECD	Yes
Finland	1965, 1970	Economic Commission for Europe, Standardized input-output tables of ECE countries ..., New York, United Nations, various years	Yes
Finland	1995-2007, annual	Eurostat, GTAP5	Yes
Fiji	1972	UNIDO, Input-output tables for developing countries, New York : United Nations, 1985	Yes
France	1959,1965, 1970, 1975	Economic Commission for Europe, Standardized input-output tables of ECE countries ..., New York, United Nations, various years	Yes
France	1972, 1977, 1980, 1985, 1990, 1995-2007	OECD, GTAP5, Eurostat	Yes
United Kingdom	1963	Economic Commission for Europe, Standardized input-output tables of ECE countries for years around 1959, New York, United Nations, 1972	No, major errors
United Kingdom	1968, 1969, 1975	Economic Commission for Europe, Standardized input-output tables of ECE countries ..., New York, United Nations, various years	Yes
United Kingdom	1979, 1984, 1990, 1995, 1997, 1998, 2000, 2003	OECD, GTAP5, Eurostat	Yes
Germany	1959, 1965, 1970, 1975	Economic Commission for Europe, Standardized input-output tables of ECE countries ..., New York, United Nations, various years	Yes
Germany	1978, 1986, 1988, 1990, 1995, 1997, 2000-2007	OECD, GTAP5, Eurostat	Yes
Ghana	1968	UNIDO, Input-output tables for developing countries, New York : United Nations, 1985	Yes

Greece	1958, 1970	Economic Commission for Europe, Standardized input-output tables of ECE countries ..., New York, United Nations, various years	Yes
Greece	1994, 1995, 1997, 1999, 200, 2005	OECD, GTAP5, Eurostat	Yes
Guatamala	1971	United Nations Economic Commission for Latin America, Tablas de insumo-producto en America Latina, Santiago de Chile : Naciones Unidas, 1983	Yes
Haiti	1971	United Nations Economic Commission for Latin America, Tablas de insumo-producto en America Latina, Santiago de Chile : Naciones Unidas, 1983	No, missing domestic gross output
Haiti	1975	United Nations Economic Commission for Latin America, Tablas de insumo-producto en America Latina, Santiago de Chile : Naciones Unidas, 1983	Yes
Hong Kong	1997	GTAP5	
Hungary	1959	Economic Commission for Europe, Standardized input-output tables of ECE countries for years around 1959, New York, United Nations, 1972	No, missing domestic gross output
Hungary	1965, 1976	Economic Commission for Europe, Standardized input-output tables of ECE countries ..., New York, United Nations, various years	Yes
Hungary	1997, 1998, 2000, 2005	OECD, GTAP5	Yes
Indonesia	1971	Biro Pusat Statistik, Tabel Input-Output Indonesia, 1971	No, missing domestic gross output
Indonesia	1975	UNIDO, Input-output tables for developing countries, New York : United Nations, 1985	Yes
Indonesia	1980	Biro Pusat Statistik, Tabel Input-Output Indonesia, 1980	No, missing domestic gross output
Indonesia	1985, 1998, 2005	Biro Pusat Statistik, Tabel Input-Output Indonesia, various years	Yes
Indonesia	1995, 1997, 2000	OECD, GTAP5	Yes

India	1973	UNIDO, Input-output tables for developing countries, New York : United Nations, 1985	Yes
India	1993, 1997, 1998, 2003	OECD, GTAP5	Yes
Ireland	1964, 1969	Economic Commission for Europe, Standardized input-output tables of ECE countries ..., New York, United Nations, various years	Yes
Ireland	1997, 1998, 2000, 2005	OECD, GTAP5	Yes
Iran	2001	http://www.amar.org.ir	Yes
Israel	1968, 1972	David Chen, Input-output tables 1968/69, Jerusalem : Bureau of Stats, 1975, 1979	Yes
Israel	1995, 2004	OECD	Yes
Italy	1959, 1965, 1970, 1975	Economic Commission for Europe, Standardized input-output tables of ECE countries ..., New York, United Nations, various years	Yes
Italy	1985, 1992, 1995, 1997, 2000, 2004, 2005	OECD, GTAP5, Eurostat	Yes
Japan	1960	Economic Commission for Europe, Standardized input-output tables of ECE countries for years around 1959, New York, United Nations, 1972	No, missing domestic gross output
Japan	1965, 1970, 1975	Economic Commission for Europe, Standardized input-output tables of ECE countries ..., New York, United Nations, various years	Yes
Japan	1980, 1985, 1990, 1995, 1996, 1997, 2000, 205	OECD, GTAP5	Yes
Kenya	1967,1971, 1976	Input/Output Table for Kenya, Central Burea of Statistics, various years	Yes
Korea	1970, 1973, 1975, 1978, 1980, 1983, 1985-1988, 1990, 1993, 1995, 1998, 2000, 2003, 2005	Bank of Korea, GTAP5	Yes

Sri Lanka	1997	GTAP5	Yes
Lithuania	2000, 2005	OECD	Yes
Luxembourg	1995, 1997, 2000, 2005	OECD, GTAP5	Yes
Latvia	1996, 1998	OECD	Yes
Morocco	1975	UNIDO, Input-output tables for developing countries, New York : United Nations, 1985	Yes
Morocco	1997	GTAP5	Yes
Madagascar	1973	UNIDO, Input-output tables for developing countries, New York : United Nations, 1985	No, missing trade and transport
Mexico	1950, 1960	United Nations Economic Commission for Latin America, Tablas de insumo-producto en America Latina, Santiago de Chile : Naciones Unidas, 1983	Yes
Mexico	1970, 1980	Banco de Mexico	Yes
Mexico	19,972,003	OECD, GTAP5	Yes
Macedonia	2005	OECD	Yes
Malta	1971	UNIDO, Input-output tables for developing countries, New York : United Nations, 1985	Yes
Malaysia	1978, 1983, 1987, 1991	Jadual input-output Malaysia, Kuala Lumpur : Jabatan Perangkaan, various years	Yes
Malaysia	1997	GTAP5	Yes
Malawwi	1997	GTAP5	Yes
Mozambique	199	GTAP5	Yes
Nicaragua	1974	UNIDO, Input-output tables for developing countries, New York : United Nations, 1985	Yes
Netherlands	1959, 1965, 1970, 1975	Economic Commission for Europe, Standardized input-output tables of ECE countries ..., New York, United Nations, various years	Yes
Netherlands	1972, 1977, 1981, 1986, 1995-2005	OECD, GTAP5, Eurostat	Yes
Norway	1959, 1965, 1970, 1975	Economic Commission for Europe, Standardized input-output tables of ECE countries ..., New York, United Nations, various years	Yes

Norway	1992-2005	Eurostat	Yes
Norway	1995, 2000	OECD	Yes
New Zealand	1995, 1997, 2002	OECD, GTAP5	Yes
Peru	1955, 1963, 1968	United Nations Economic Commission for Latin America, Tablas de insumo-producto en America Latina, Santiago de Chile : Naciones Unidas, 1983	Yes
Peru	1997	GTAP5	Yes
Philippines	1974	UNIDO, Input-output tables for developing countries, New York : United Nations, 1985	No, missing domestic gross output
Philippines	1997	GTAP5	
Papua New Guineau	1972	UNIDO, Input-output tables for developing countries, New York : United Nations, 1985	Yes
Poland	1962, 1967, 1977	Economic Commission for Europe, Standardized input-output tables of ECE countries ..., New York, United Nations, various years	Yes
Poland	1995, 1997, 2000, 2004, 205	OECD, GTAP5	Yes
Portugal	1959, 1965, 1970, 1974	Economic Commission for Europe, Standardized input-output tables of ECE countries ..., New York, United Nations, various years	Yes
Portugal	1995, 1997, 1999, 2000, 2005	OECD, GTAP5, Eurostat	Yes
Romania	2000, 2003-2005	Eurostat	Yes
Russia	1995, 2000	OECD	Yes
Russia	2002	OECD	No, major errors
Rwanda	1970	UNIDO, Input-output tables for developing countries, New York : United Nations, 1985	Yes
Senegal	1959	UNIDO, Input-output tables for developing countries, New York : United Nations, 1985	Yes
Singapore	1973	UNIDO, Input-output tables for developing countries, New York : United Nations, 1985	Yes

Singapore	1997	GTAP5	
Slovakia	1995, 2000, 200	OECD, Eurostat	Yes
Slovenia	1996, 2000, 2001, 2005	Eurostat	Yes
Sweden	1964, 1969, 1975	Economic Commission for Europe, Standardized input-output tables of ECE countries ..., New York, United Nations, various years	Yes
Sweden	1995, 1997, 2000, 2005	GTAP5, Eurostat	Yes
Thailand	1975	UNIDO, Input-output tables for developing countries, New York : United Nations, 1985	Yes
Thailand	1997	GTAP5	Yes
Turkey	1963	Economic Commission for Europe, Standardized input-output tables of ECE countries for the years around 1959, New York, United Nations, 1972	No, missing domestic gross output
Turkey	1968	Economic Commission for Europe, Standardized input-output tables of ECE countries for the years around 1970, New York, United Nations, 1982	Yes
Turkey	1973	Economic Commission for Europe, Standardized input-output tables of ECE countries for the years around 1975, New York, United Nations, 1982	Yes
Turkey	1996, 1997 1998, 2002	OECD, GTAP5	Yes
Taiwan	1971	UNIDO, Input-output tables for developing countries, New York : United Nations, 1985	Yes
Taiwan	1981, 1984, 1986, 1989, 1991, 1994, 1999, 2004	http://eng.stat.gov.tw/	Yes
Taiwan	1996, 1997, 2001, 2006	OECD, GTAP5	Yes
Tanzania	1970	UNIDO, Input-output tables for developing countries, New York : United Nations, 1985	Yes
Tanzania	1997	GTAP5	Yes
Uganda	1997	GTAP5	Yes

Uruguay	1961	United Nations Economic Commission for Latin America, Tablas de insumo-producto en America Latina, Santiago de Chile : Naciones Unidas, 1983	No, missing mining sectors
Uruguay	1997	GTAP5	Yes
United States	1958, 1963	Economic Commission for Europe, Standardized input-output tables of ECE countries ..., New York, United Nations, various years	No, missing domestic gross output
United States	1972, 1977, 1982	BEA	Yes
United States	1985, 1990, 1995, 1997, 2000, 2005	OECD, GTAP5	Yes
USSR	1966	Economic Commission for Europe, Standardized input-output tables of ECE countries for the years around 1965, New York, United Nations, 1977	No, missing domestic gross output and F vector
Venezuela	1997	GTAP5	Yes
Vietnam	1997	GTAP5	Yes
Yugoslavia	1962, 170, 1976	Economic Commission for Europe, Standardized input-output tables of ECE countries ..., New York, United Nations, various years	Yes
Yugoslavia	1966	Economic Commission for Europe, Standardized input-output tables of ECE countries for the years around 1965, New York, United Nations, 1977	No, missing sectors
South Africa	1971, 1975, 1978, 1981, 1984, 1988, 1989, 1993	ZAF stat	Yes
South Africa	2000, 2005	OECD	Yes
Zambia	1973	UNIDO, Input-output tables for developing countries, New York : United Nations, 1985	No, missing domestic gross output
Zambia	1997	GTAP5	Yes
Zimbabwe	1997	GTAP5	Yes

Notes The table lists each IO table we collected (excluding those in GTAP7, which are listed above in Table 11), its source, and whether or not it is included in the sample. If not, we provide a brief description of why it was not. “Major errors” means that we discovered significant errors in the original sources that proved impossible to correct. Generally tables that were missing some major sectors were excluded, as were those that did not provide a measure of domestic gross output. GTAP5 is the major source of tables for 1997.

Table 13: GTAP Sectors and Abbreviations

Code	Description	Code	Description	Code	Description
PDR	Paddy rice	**OMT**	Meat products nec	**OTN**	Transport equipment nec
WHT	Wheat	**VOL**	Vegetable oils and fats	**ELE**	Electronic equipment
GRO	Cereal grains nec	**MIL**	Dairy products	**OME**	Machinery and equipment nec
V_F	Vegetables, fruit, nuts	**PCR**	Processed rice	**OMF**	Manufactures nec
OSD	Oil seeds	**SGR**	Sugar	**ELY**	Electricity
C_B	Sugar cane, sugar beet	**OFD**	Food products nec	**GDT**	Gas manufacture, distribution
PFB	Plant-based fibers	**B_T**	Beverages and tobacco products	**WTR**	Water
OCR	Crops nec	**TEX**	Textiles	**CNS**	Construction
CTL	Bovine cattle, sheep and goats, horses	**WAP**	Wearing apparel	**TRD**	Trade
OAP	Animal products nec	**LEA**	Leather products	**OTP**	Transport nec
RMK	Raw milk	**LUM**	Wood products	**WTP**	Water transport
WOL	Wool, silk-worm cocoons	**PPP**	Paper products, publishing	**ATP**	Air transport
FRS	Forestry	**P_C**	Petroleum, coal products	**CMN**	Communication
FSH	Fishing	**CRP**	Chemical, rubber, plastic products	**OFI**	Financial services nec
COA	Coal	**NMM**	Mineral products nec	**ISR**	Insurance
OIL	Oil	**I_S**	Ferrous metals	**OBS**	Business services nec
GAS	Gas	**NFM**	Metals nec	**ROS**	Recreational and other services
OMN	Minerals nec	**FMP**	Metal products	**OSG**	Public Administration, Defense, Education, Health
CMT	Bovine meat products	**MVH**	Motor vehicles and parts		

Source: https://www.gtap.agecon.purdue.edu