Linkages and Economic Development

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Abstract

We construct a database of input-output tables covering a broad spectrum of countries and times and document a strong and robust positive correlation between the strength of industry linkages and aggregate productivity. We then calibrate a multisector neoclassical model and 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 the welfare gains from eliminating these distortions are modest but significant, averaging roughly 7% of initial welfare. Poor and middle-income countries tend to have higher gains, averaging about 11%. The gains are largely driven by distortions in the manufacturing and service sectors, which have strong domestic forward linkages with the rest of the economy.

Keywords: productivity, input-output tables, distortions
JEL codes: O11, C67, O47

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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 that 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. More recent work (e.g. Ciccone (2002), Acemoglu et al. (2007), Jones (2011), Baqaee and Farhi (2020)) 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.

The 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 228 country-year observations (with 63 unique countries) at different levels of development (from Uganda to the USA) and in different time periods (from the 1950s to the present). For example, our database includes such rare gems as input-output tables for Bolivia in 1958, Bulgaria in 1963 and Senegal in 1974. These input-output tables come from national statistical offices and central banks, various international statistical agencies (e.g. the OECD, Eurostat, United Nations), and the academic literature. As we show in the paper, this broad time-series and cross-sectional coverage is essential for identifying the systematic relationship between linkages and development.

Our database represents the most extensive centralized electronic collection of original IO tables in existence. It differs from global input-output tables (e.g. the World Input-Output Database (WIOD,

[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." Source: http://www.thehenryford.org/rouge.

Timmer et al. (2015)) and the Global Trade Analysis Project (GTAP, Aguiar et al. (2019)) in two key respects. First, our data has a much longer time horizon. This feature of our data gives us the unique ability to examine the systematic time-series variation in IO tables within countries over the long run. Second, global input-output tables are not repositories of original IO tables but rather internally consistent representations of the entire global economy at a point in time (and in some cases over time). Achieving this global internal consistency from highly heterogeneous (in terms of both existence and quality) and often contradictory sources requires imputations and adjustments to the original data using complex algorithms, rendering the use of the results as "data" for cross-country and especially time series comparisons of IO tables problematic.

We use a simple framework in the spirit of Jones (2011) 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 propose the *Average Output Multiplier* (AOM), computed from the observed input-output table, as a summary measure of the strength of domestic aggregate linkages. We show that the average output multiplier is robustly positively correlated with aggregate productivity, as measured by log output per worker, in both the cross-section and the time series. A standard deviation increase in AOM is associated with an increase in log output per worker of between 0.2 and 0.6 standard deviations, with the lower estimate coming from estimates using exclusively the time series variation within countries. We further decompose the AOM into forward linkages by sector and find that forward linkages in the manufacturing and service sectors in particular are strongly positively correlated with aggregate productivity. We find that these relationships are driven by the presence of poor countries in the sample; within rich countries alone, differences in aggregate linkages are not strongly associated with productivity differences.

Motivated by these findings, we build a static open-economy version of the Long and Plosser (1983) multisector neoclassical model with an input-output loop and misallocation in the market for intermediate goods, similar to Jones (2013). We take the traditional development accounting perspective that undistorted factor shares are similar across countries, and thus that cross-country differences in IO tables are due to distortions. Our baseline identification assumption is that the U.S. input-output table is undistorted, and we show how to use the structure of the model and the input-output data to identify the implied distortions in other countries. We then compute the welfare gains from eliminating distortions and assess the contribution of distortions to explaining the observed cross-country differences in output per worker.

We find that eliminating distortions entirely would result in gains of roughly 7% of initial welfare for the average country in the sample, rising to about 12% for countries at the 90$^{\text{th}}$ percentile and up to 50% for the most distorted economies. Most rich countries would gain little from eliminating distortions, reflecting their relatively low levels of misallocation, while many poor countries would gain substantially. Consistent with our empirical findings, the largest gains tend to come from eliminating distortions in the manufacturing and service sectors. We also find that the relationship between AOM and the gains from eliminating distortions in our model is similar to the empirical relationship between AOM and aggregate productivity 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 aggregate productivity.

Our paper contributes to the reviving literature on intermediate goods linkages and economic development. Theoretically, Jones (2011) 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. Other related theoretical contributions on how microeconomic distortions affect and are propagated through production networks include Rodriguez-Clare (1996), Grossman and Helpman (2002), Acemoglu et al. (2007), Oberfield (2018), Liu (2019), Baqaee and Farhi (2020) and Osotimehin and Popov (2023). Recent quantitative work that studies the effects of one or more distortions on aggregate productivity and welfare include Fadinger et al. (2021), Boehm and Oberfield (2020), Boehm (2022), and Caliendo et al. (2022). Relative to this literature, our paper focuses more on establishing basic cross-country empirical patterns in intermediate goods linkages and quantifying the impacts of a broad set of distortions empirically in a new, more comprehensive cross-country dataset. 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) and Deutsch and Syrquin (1989).

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 the 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. (2014) 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 (reviewed in Herrendorf et al. (2014)). Rather than study how the composition of output change 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. Theoretical Framework

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. In general, the 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.[3]

If we divide each column j of $\mathbf{D}$ by the gross output in industry j we obtain the *technical matrix* $\mathbf{A}$, which provides a summary of the linkages between different production units in the economy. Larger entries in $\mathbf{A}$ indicate a greater amount of input trade between plants. In this sense $\mathbf{A}$ 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 (2011, 2013), 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 (2011) shows that these types of distortions generate inefficiencies in the presence of intermediate goods linkages, 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, different industries, 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 transacting across firms difficult and

[3] 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.

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 channels as an implicit tax on intermediate inputs.[4]

2.1 Single Sector Model

We can use a simple model of a closed economy with a single sector to illustrate how these forces affect the entries in the IO table. Suppose the representative firm hires labor and purchases intermediate inputs to produce its output using the production function

$$Y = (AL)^{\alpha} \cdot M^{1-\alpha} \tag{2.1}$$

where M is the intermediate input, L is labor input and A is the labor augmenting technology level. The firm sells its output to both other firms and consumers in a competitive market. However, the firm faces a tax of τ^Y percent on each unit of output it produces. It also faces a tax τ^M on the value of intermediate inputs that it purchases. As in Hsieh and Klenow (2009), τ^M and τ^Y represent the effect of a host of complex microeconomic distortions that could affect input and output markets.[5] In the context of our discussion above, τ^Y captures the first connection between IO structure and economic development and τ^M captures the second connection.

The firm's maximization problem is

$$\max_{L,M} (1 - \tau_j^Y)PY - wL - (1 + \tau^M)PM. \tag{2.2}$$

The firm's first order condition with respect to M can be rearranged to yield the (in this case single) entry of the (observed) IO matrix $\mathbf{A} = a$,

$$a \equiv \frac{PM}{PY} = \frac{1-\alpha}{t}, \tag{2.3}$$

where $t \equiv \frac{1+\tau^M}{1-\tau^Y}$. Distortions that act as taxes on revenue or intermediate input usage reduce the size of the input-output coefficient, and this conclusion generalizes to multi-sector models and models with CES production functions (see Section 5 and Appendix A).[6] This makes statistics based on the entries of the IO table potentially powerful indicators of the presence of distortions in the economy.

[4]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.

[5]More explicit models of input markets with specific sources of distortions can be found in, for example, Acemoglu et al. (2007), Oberfield (2018), Boehm (2022) and Boehm and Oberfield (2020).

[6]This conclusion assumes that the implicit tax τ^M is not included in the intermediate goods price that is recorded in the national accounts. We discuss the role of accounting in the measurement of distortions further in Section 5.

However, we cannot distinguish between these two types of distortions based on the entries of $\mathbf{A}$ because they have the same effect on the IO coefficient. Furthermore, without additional information, we cannot separate the technological factor share $(1-\alpha)$ from the distortion, even in the special case of the Cobb-Douglas production function. We will return to these points below, but first we examine how distortions affect productivity.

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,

$$VA = Y - M = L \underbrace{\left[A \left(\frac{1-\alpha}{t} \right)^{\frac{1-\alpha}{\alpha}} \left(1 - \frac{1-\alpha}{t} \right) \right]}_{\text{TFP}} \tag{2.4}$$

where the term in brackets is the measured TFP using the value-added production function. Measured TFP is negatively affected by the presence of distortions ($t \neq 1$), with the effect of both types of distortions captured by the value of t. Measured TFP is maximized when $t = 1$. 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.[7]

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, in accordance with the general principle that the marginal welfare loss due to a distortionary tax is increasing in the size of the tax. Second, the productivity losses from distortions are bigger when the intermediate share is 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 (Jones, 2013).

2.2 Identifying distortions and their effects

The theory above gives simple and clear predictions for how distortions affect the entries of the IO matrix and aggregate productivity. These predictions generalize to models with multiple sectors and international trade, as we show in Section 5. However, in practice, there are several challenges to quantifying the presence and impact of these distortions in the data. One issue is that the simple linkage between distortions and the IO coefficients in equation (2.3) 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 sectoral prices will also enter into the expression for the IO coefficient. The exact relationship between the size of frictions, the observed IO coefficients and the impact of distortions on productivity depend on the details of the model.[8] Data

[7]In a model with capital accumulation, the negative effect of distortions is further amplified in the long run.

[8]Osotimehin and Popov (2023) find that lower EoS between different intermediate inputs dampens the effects of distortions on aggregate productivity,conditioning on the size of the distortion. However, the inferred distortion given the IO coefficient will be larger and hence the net effect is not clear. It is also easy to show that lowering the elasticity of substitution

constraints, in particular the lack of comparable cross-country data on sector-level relative prices, limit our ability to explore the quantitative implications of non-Cobb-Douglas domestic technologies in the data. However, alternative models make similar qualitative predictions that higher distortions lead to lower observed intermediate shares and that the effects of distortions are transmitted and amplified by the IO network.

The other important issue is that the technological intermediate share α (more generally α_{sj}) may vary across countries, so we might have trouble distinguishing between cross-country differences in distortions and differences in technology. Variation in α_{sj} 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 principle, the same underlying forces that generate the distortions (e.g. cost of contract enforcement) might be causally related or simply correlated with factors that influence the available technology as well. As a result, the conceptual distinction between "technology" and "distortions" may be somewhat blurry in practice.

In light of these constraints, our goal in this paper is to take a modest first step towards assessing the potential of distortions in the production network to help explain cross-country differences in aggregate productivity. To this end, we have collected, digitized and standardized a dataset of IO tables that is unprecedented in its coverage, especially in the time-series dimension (see Section 3 below). We use this panel of IO tables to document some basic facts of how the IO network varies across countries and within countries over time, focusing on correlations with log output per worker. We then take an approach akin to development accounting (Hall and Jones, 1999) to structurally identify country-sector-level distortions and compute the gains from eliminating them in a quantitative multisector model.

2.3 Measuring the Strength of Linkages

Our empirical analysis in Section 4 examines cross-country and within-country, over time variation in the entries of the IO table, which represent the strength of direct input linkages between two sectors. It is also useful to have a measure of the total strength of the linkages embodied in a given IO table. Our primary measure of the aggregate strength of linkages is the "Average Output Multiplier" (AOM), defined as

$$AOM = \frac{1}{N}\iota^T(\mathbf{I}-\mathbf{A})^{-1}\iota \tag{2.5}$$

where ι is a vector of ones and N is the number of sectors. The matrix $\mathbf{\Lambda} = (\mathbf{I}-\mathbf{A})^{-1}$ is the *Leontief inverse* of the input-output matrix, which has several economic interpretations. In an accounting sense, the ijth entry is the derivative of gross output in sector i with respect to final demand in sector j, taking into account both direct and indirect linkages. In a competitive undistorted economy, the ijth entry is also the elasticity of price in sector j with respect to a (gross output) productivity shock in sector i, holding factor prices fixed. The AOM can therefore be interpreted as either the average

between labor and the intermediate bundle tends to amplify the negative effects of distortions.

change in gross output implied by a uniform increase in final demand, or as the average elasticity of sectoral prices with respect to an aggregate (gross output) productivity shock.

The AOM has a number of attractive features as a summary measure of linkages and distortions. It is increasing in α_{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. Moreover, it can naturally be decomposed into the constituent row or column sums of Λ, which can be interpreted as the total forward linkages or backward linkages associated with the row or column industry, respectively.[9]

While AOM is a natural summary measure of aggregate linkages, many other measures have been proposed in the literature (see Miller and Blair (2009) for additional examples and discussion). One simple alternative is the "Mean Direct Linkages" (MDL), defined as the average row (or column) sum of the technical matrix $\mathbf{A}$. The row (column) sums of this matrix can be interpreted as the direct forward (backward) linkages generated by a sector. This measure does not account for indirect linkages but has the virtue of being able to incorporate imported inputs in a straightforward way. Another possibility is a final demand-weighted version of AOM, which we call $WAOM$, which replaces ι^T in equation (2.5) with a vector of final demand weights. This measure can be shown to equal the reciprocal of 1 minus the aggregate domestic intermediate share. However, this and other conceptually similar weighted measures mix information on what is produced with how it is produced, which complicates its interpretation since different sectors may be naturally more intermediate-intensive than others. Our main empirical analysis focuses on AOM and its components, with results for other measures discussed in Appendix B.

3. Data

In our empirical work, we utilize an extensive, newly assembled dataset of IO tables with coverage ranging from the 1950s to 2005. The tables are from a wide variety of sources, including large electronic collections such as the OECD historical IO statistics, national statistics offices, published academic studies and reports from international agencies. Many sources contained tables in hard copy only, requiring digitization using (double) hand entry. A series of publications by various UN agencies formed a particularly rich archive of scarce older tables for developing countries.[10]

Our search uncovered a large number of tables that are highly heterogeneous in terms of the quality of the data collection, the type of data collected, and their levels of sectoral aggregation. Some tables contained gross transcription errors or violations of adding-up constraints, which were not always possible to correct based on the other information in the table. Other tables were missing key

[9]To be precise, the ith row sum of $\frac{1}{N} \cdot \Lambda$ is the average elasticity of sectoral prices with respect to a gross output productivity shock in sector i, while the ith column is the average elasticity of price in sector i with respect to a productivity shock in other sectors. A similar interpretation holds in terms of final demand linkages.

[10]Table C in Appendix C records the full list of tables and their sources.

pieces of information, such as mining or service sectors, or the value of imported inputs separate from domestic. Some older tables did not include sectors related to distribution (e.g. wholesale/retail, transportation) as separate sectors but instead recorded payments to those sectors as a separate row without the corresponding column, usually labeled as "Trade/Transportation Margin." Since these various issues all create inconsistencies across tables that affect cross-country comparisons, we omitted tables with these issues from our empirical analysis. However, we include them in our list of sources (Appendix Table C), along with a "quality" score that indicates the source of the problem. Our empirical analysis uses only tables with a quality score of "1."[11]

Table 1: Panel: Observations by Region and Time Period

Region	1950s	1960s	1970s	1980s	1990s	2000s	Total
Africa	0	0	5	7	2	1	15
Asia	0	1	8	7	10	10	36
Easter Europe & Transition	0	1	3	0	9	17	30
Latin America	6	4	6	1	4	3	24
Western Europe & Offshoots	1	16	28	14	29	35	123
Total	7	22	50	29	54	66	228

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 1 summarizes the temporal and geographic coverage of our final sample of tables, with a total of 228 unique observations. For each table in the sample, we observe sector-level gross output, final demand, value added, the domestic IO table **D** and the total value of imported inputs used by each sector. Note that we do not generally observe the country or sector of origin for imported inputs, only the total value and the domestic using sector. We have a sizable number of tables from the 1960s and 1970s, a dip in coverage in the 1980s, and the best coverage in the 1990s and early 2000s. Coverage is worse in earlier years, especially for non-European countries. Nonetheless, developing countries have significant representation for many 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 total number of distinct countries in the sample is 67, with 48 countries having two or more observations, with the time between the first and last observation often spanning multiple decades.

To the best of our knowledge, this dataset represents the most extensive centralized electronic collection of original IO tables in existence. The most comparable datasets are those associated with efforts to build consistent global input-output models, such as the World Input-Output Database (WIOD, Timmer et al. (2015)) and the Global Trade Analysis Project (GTAP, Aguiar et al. (2019)).[12] Our dataset differs from these in several key respects. First, our data has a much longer time horizon;

[11]One additional issue is that we occasionally encountered an embarrassment of riches, with multiple sources for tables in the same or adjacent years. In these cases we select the highest quality or most standard source, for example the OECD.

[12]Other similar datasets include the OECD's ICIO database and the EORA project.

coverage in the alternatives begins in the 1990s at the earliest. This feature of our data gives us the unique ability to examine systematic time-series variation in IO tables within countries in the long run. Second, these alternative datasets are not repositories of original IO tables but rather internally consistent representations of the entire global economy at a point in time (and in some cases over time). Achieving this global internal consistency from highly heterogeneous (in terms of both existence and quality) and often contradictory sources requires a large number of imputations and adjustments to the original data using complex algorithms.[13] While these methods are well suited to their objectives, it renders the use of the results as "data" for cross-country and especially time-series comparisons of IO tables problematic.[14]

Our empirical analysis requires that we use a common and consistent level of sectoral aggregation across countries and over time. Individual coefficients from IO tables at different levels of sectoral aggregation are obviously not comparable; neither are aggregate statistics such as the AOM. We aggregate each table into four broad sectors: agriculture, manufacturing, services, and a residual sector comprising mining, utilities and construction (MCU).[15] There is broad agreement between the two measures (see Figure A1 in Appendix B), with an R^2 of 0.60, suggesting that our relatively coarse aggregation scheme preserves much of the information in the original tables. However, there is a noticeable tendency for aggregation to raise the AOM of countries with low AOM relative to countries with high AOM. This is in part due to the tendency for tables with more highly disaggregated sectors to yield higher values of AOM (Figure A2 in Appendix B.1). Our aggregation scheme guards against the possibility that correlations between the AOM and aggregate productivity are driven by systematic differences in sectoral classifications across rich and poor countries.

4. Empirics

In this section, we document some basic facts about our data. We focus on the cross-sectional and panel variation in linkages to illustrate not only the diversity of IO structures in the data but also how these linkages evolve over time within countries. In addition, we examine how linkages are related to economic outcomes such as aggregate productivity.

Our measure of aggregate productivity is the log of real output per worker from the Penn World Tables, version 9.1 (Feenstra et al., 2015).[16] This measure is highly correlated with alternatives such as total factor productivity and is available for a larger number of countries and time periods. This variable is not available for some countries for which we have IO tables, and we thus exclude these

[13]For details on this process, see for example the documentation of the GTAP10 database at https://www.gtap.agecon.purdue.edu/databases/v10/v10_doco.aspx.

[14]Annual time series of IO tables spanning decades are created from an often small number of original tables, by interpolation and imputation using macroeconomic data.

[15]Formally, let x be the dimension of the original table and let $\mathbf{C}$ be the 4 by x 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 4 by 4 aggregated matrix is $\mathbf{D}_4 = \mathbf{C}\mathbf{D}\mathbf{C}^T$.

[16]Specifically, for regressions without country fixed effects we use the log of $rgdpo/emp$, while for regressions with country fixed effects we use the log of $rgdpna/emp$.

countries from our analysis in this section.

To further strengthen the cross-country comparability of IO linkages, we restrict the sample to exclude countries with histories of strong central planning, primarily in Eastern Europe and the former Soviet Union (as well as China). Theoretically, it is unclear how to compare IO tables constructed from transactions at market prices to those from non-market economies. Empirically, countries with a history of central planning exhibit striking systematic differences in linkage measures compared to market economies, both in levels and in their dynamics over the course of their transition to market economies in the 1990s and early 2000s. Appendix B documents some of these differences and provides a brief discussion. After applying these two sample selection criteria, our final sample for analysis contains 199 observations from 51 countries, with 36 countries having two or more observations.[17]

4.1 Basic properties of IO linkages

Table 2: IO Coefficients: Means and Standard Deviations

		Using Sector			
		Agriculture	Manufacturing	Services	Min., Con. & Utilities
Producing Sector	Agriculture	0.11	0.08	0.01	0.01
		(0.07)	(0.06)	(0.02)	(0.01)
	Manufacturing	0.15	0.23	0.07	0.19
		(0.07)	(0.08)	(0.03)	(0.08)
	Services	0.10	0.13	0.18	0.13
		(.06)	(.05)	(.07)	(.05)
	Min., Con. & Utilities	0.02	0.04	0.03	0.09
		(0.02)	(0.02)	(0.01)	(0.07)
	Imported Inputs	0.05	0.18	0.05	0.08
		(0.05)	(0.09)	(0.05)	(0.06)
	Total Domestic Share	0.38	0.48	0.28	0.42
		(0.13)	(0.09)	(0.07)	(0.08)
	Total Intermediate Share	0.43	0.66	0.33	0.49
		(0.14)	(0.05)	(0.08)	(0.08)
	Corr. Dom. & Imp. Inputs	0.17	-0.82	-0.10	-0.30
		(0.14)	(0.06)	(0.11)	(0.12)

Notes Unweighted averages calculated separately for each coefficient, across $N = 199$ country-year observations. Numbers in parentheses are standard deviations. Standard errors for correlations are clustered at the country level.

Table 2 computes summary statistics for the individual entries of the IO tables in our sample. Consistent with other analyses of IO linkages (e.g. Horvath (2000)), the average IO table has a strong diagonal for all sectors. The largest off-diagonal entries almost always involve either manufacturing or services as the supplier sector, underscoring the large domestic direct forward linkages generated by these sectors. The manufacturing sector also tends to generate the largest domestic direct backwards

[17]The minimum time difference between observations from the same country is 4 years.

linkages, as well as having the largest share of imported inputs. The shares of domestic and imported inputs are strongly negatively correlated in manufacturing, heuristically suggesting substantial substitutability. These correlations are much weaker for other sectors, but the overall importance of imported inputs is also much lower. Table 2 also reveals substantial cross-country and time variation in the individual IO coefficients, as well as in the total domestic and imported intermediate goods shares for each industry.

4.2 Correlation analysis

Table 3: Cross-sectional correlations with log output per worker

		Using Sector			
		Agriculture	Manufacturing	Services	Min., Con. & Utilities
Producing Sector	Agriculture	0.26	-0.50	-0.61	-0.21
		(0.10)	(0.09)	(0.09)	(0.10)
	Manufacturing	0.49	0.36	-0.33	0.13
		(0.09)	(0.14)	(0.12)	(0.12)
	Services	0.27	0.04	0.47	0.17
		(.13)	(.12)	(.11)	(.12)
	Min., Con. & Utilities	0.41	-0.18	-0.04	0.13
		(0.11)	(0.16)	(0.11)	(0.07)
	Imported Inputs	0.32	0.04	0.04	0.07
		(0.11)	(0.15)	(0.09)	(0.13)

Notes Standardized coefficients from residualized regressions controlling for time FE and imported inputs. 199 observations.

We now examine the empirical relationship between the observed dispersion in IO linkages and aggregate productivity. We first examine cross-sectional correlations by regressing log output per worker for country c on each cost share of industry i for industry j in country c. We use the Frisch-Waugh-Lovell theorem to partial out decade fixed effects (to control for trends in the data) and the share of imported inputs (to control for varying degrees of openness to international trade), and standardize the coefficients to enhance comparability across sectors.[18] We cluster the standard errors at the country level.

We find (Table 3) that larger values of the domestic diagonal entries (e.g., agriculture-to-agriculture cost share) are robustly associated with greater output per worker in all industries. For example, an increase of 1 standard deviation in the service-to-service cost share is associated with an increase in log output per worker equal to roughly 1/2 of a standard deviation. For the off-diagonal domestic coefficients, the pattern is decidedly mixed. Generally, direct domestic forward linkages from manufacturing and services (i.e. when these sectors act as suppliers) are positively associated with log output per worker, although the strength of the relationship varies across buying sectors (and is

[18]In this and the following exercises, we generally find similar results when we do not control for time fixed effects and import shares.

negative for manufacturing-to-services). This pattern 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. Off-diagonal entries for which agriculture is the buying sector also have strong positive correlations with log output per worker. In contrast, we observe strong negative correlations for off-diagonal linkages in which agriculture is the supplier sector. The use of imported inputs tends to be only weakly associated with aggregate productivity, with the exception of the agricultural sector.

Table 4: Panel correlations with log output per worker

		Using Sector			
		Agriculture	Manufacturing	Services	Min., Con. & Utilities
Producing Sector	Agriculture	-0.17	-0.44	-0.09	-0.23
		(0.09)	(0.11)	(0.10)	(0.17)
	Manufacturing	0.32	0.30	-0.05	-0.03
		(0.19)	(0.18)	(0.08)	(0.11)
	Services	0.29	0.12	0.21	-0.07
		(.12)	(.21)	(.09)	(.11)
	Min., Con. & Utilities	0.12	-0.26	0.03	0.08
		(0.09)	(0.14)	(0.06)	(0.11)
	Imported Inputs	0.02	0.02	0.00	0.24
		(0.11)	(0.19)	(0.10)	(0.09)

Notes Standardized coefficients from residualized regressions, controlling for time FE, country FE and imported inputs. 179 observations.

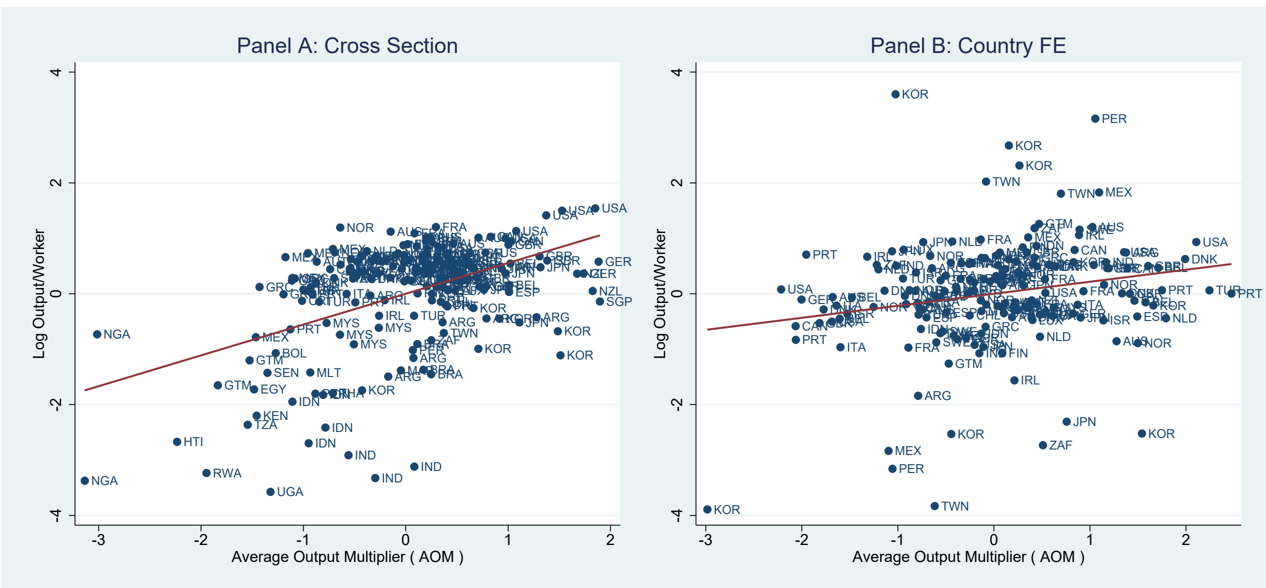
Cross-sectional comparisons of macroeconomic outcomes are notoriously subject to concerns regarding confounding factors that are omitted from the analysis. One of the valuable aspects of our data is that we can partially ameliorate some of these concerns by looking at the comovement between output per worker and IO linkages within countries, over time, by adding country fixed effects to our specification.[19] Table 4 reports the results. On the whole, the inclusion of country fixed effects somewhat weakens the correlations between productivity and individual IO coefficients, which is consistent with either omitted time-invariant variables or increased attenuation due to measurement error. However, reassuringly the qualitative patterns of correlations are broadly similar to those found in the cross-sectional analysis.

While the results in Tables 3 and 4 are informative about the relationship between individual linkages and productivity, they do not take into account either within-country correlations between IO coefficients or the importance of individual linkages in the overall IO network. As argued in Section 2, the AOM is a simple measure of the strength of aggregate linkages that does account for

[19]One issue with this approach is that our panel is unbalanced, which implies that the comparison groups differ across time. If observations are not missing at random then our estimates could be subject to bias, although the direction of the bias is not clear and the proportion of rich and poor countries in each time period (except for the 1950s, which has few observations) is roughly similar. We have examined various subsamples and found similar results (not reported) to our main specification.

these factors. In our next exercise, we use regressions of the same form as above (partialling out time/country fixed effects and total imported inputs, standardized coefficients) but with the AOM as the independent variable. Figure 1 plots the results for the cross-section and panel specifications. We observe a very strong positive relationship between the AOM and log output per worker in the cross-section (Panel A); a standard deviation increase in AOM is associated with an increase of 0.56 standard deviations in log output per worker, with an R^2 of 0.23. Interestingly, a visual inspection of the figure suggests that this strong positive slope is driven by comparisons between poor and middle-income countries vs. rich countries. The variation in aggregate linkages within rich countries only is not strongly associated with productivity, a finding that echoes that of Jones (2013). This highlights the importance of including poor and middle-income countries in the analysis.

Figure 1: AOM and Log Output/Worker



Notes Standardized coefficients from residualized regressions, controlling for time FE and imported inputs in Panel A, adding country FE in panel B.

Panel B of Figure 1 plots the relationship between the AOM and productivity when using only within-country variation. We continue to see a positive relationship, but the magnitude of the regression coefficient is much lower; a standard deviation increase in the AOM is associated with an increase of 0.22 standard deviations in log output per worker, with an R^2 of 0.06.[20] While the average relationship between productivity growth and growth in domestic linkages is positive, there is clearly substantial heterogeneity in the development paths of different countries with respect to the role of domestic linkages. Panel A of Table 5 reports the regression coefficients and standard errors associated with Figure 1, as well as regressions without controlling for imported inputs. The coefficient on imported inputs is positive and sizable, indicating that development is associated with

[20]As in the individual coefficient analysis, this pattern could be driven by either omitted time-invariant variables or attenuation due to measurement error.

increased use of both domestic and imported inputs. Moreover, controlling for imported inputs tends to strengthen the positive correlation between AOM and productivity due to the negative correlation between domestic linkages and imported inputs.

As discussed in Section 2, a convenient feature of the AOM is that it can be decomposed into the total forward (backward) linkages generated by each sector using the row (column) sums of the matrix Λ. Panel B of Table 5 reports the results of allowing the coefficients on each row sum of Λ, the sum of which is equal to the AOM, to vary across sectors. In both the cross-section and the panel specifications we observe a strong positive association between log output per worker and forward linkages in manufacturing and services, a strong negative association with forward linkages in agriculture, and a weak association with forward linkages in MCU. Accounting for this sectoral heterogeneity increases the fit of the model substantially; for example, the R^2 in the panel specification (column 4) increases from 0.06 to 0.26 when moving from Panel A to Panel B.[21]

Table 5: AOM and Log Output/Worker

	Log Output/Worker			
	Panel A: AOM			
AOM	0.35	0.56	0.17	0.22
	(0.11)	(0.12)	(0.08)	(0.08)
Imported Inputs Share		0.40		0.19
		(0.11)		(0.12)
R^2	0.12	0.23	0.03	0.06
	Panel B: Forward Linkages			
Agriculture	-0.17	-0.03	-0.37	-0.34
	(0.10)	(0.08)	(0.10)	(0.11)
Manufacturing	0.17	0.26	0.31	0.31
	(0.10)	(0.09)	(0.18)	(0.17)
Services	0.32	0.47	0.26	0.28
	(0.11)	(0.12)	(0.11)	(0.12)
Mining, Cons. and Utilities	0.09	0.09	-0.09	-0.08
	(0.09)	(0.08)	(0.08)	(0.08)
Imported Inputs Share		0.38		0.09
		(0.10)		(0.11)
R^2	0.21	0.30	0.25	0.26
Number of Observations	199	199	179	179
Country FE	No	No	Yes	Yes

Notes Standardized coefficients from residualized regressions, controlling for time FE and imported inputs (plus country FE in columns (3) and (4). Panel B is the same specification as in Panel A, except that the coefficients on the separate row sums comprising the AOM are allowed to vary across sectors.

These results are quite robust to alternative estimators/estimands that are less sensitive than

[21] One can do the same exercise with backward linkages, but we find generally weak correlations when decomposing aggregate linkages in this way.

OLS to outliers (such as the conditional median estimated via LAD). They are also robust to using alternative measures such as the Mean Direct Linkage (MDL). Qualitatively, the results are also robust to using the final demand weighted version of the AOM (the $WAOM$), which is equivalent to the reciprocal of 1 minus the aggregate domestic intermediate share. However, the relationships are considerably weaker from a statistical perspective. The source of the difference is that richer countries on the whole tend to specialize in the service sector, which has a low overall intermediate share, and hence a higher weight in the construction of $WAOM$. As discussed in Section 2, the fact that the $WAOM$ is influenced by the sectoral composition of final demand makes it more difficult to interpret. We report the results discussed here in Appendix B.

4.3 Discussion

Our analysis finds robust correlations between IO linkages and economic development: stronger linkages are generally positively associated with greater output per worker, with forward linkages in manufacturing and services driving the positive relationship and forward linkages in agriculture exhibiting a negative association with output per worker. Obviously, these patterns do not imply any particular causal relationship between the two variables. Apart from issues of omitted variables that are endemic to the cross-country regression literature, there is the question of whether cross-country differences in IO tables are driven by differences in technology, distortions, or relative prices across sectors. The evidence above does not provide a definitive answer to these questions. However, these reported correlations provide empirical moments which we can interpret through the lens of our model and thus provide an internally consistent reading of the empirical patterns. In the following section, we take the traditional development accounting perspective that differences in undistorted factor shares are limited across countries and then explore the welfare implications of the implied distortions. We then analyze the extent to which the welfare implications of removing distortions from our model line up with the empirical relationships between linkages and development.

5. Quantitative Exercises

This section outlines our structural model and discusses the identification of distortions and technologies as well as calibration. We use our calibrated model to quantitatively assess the magnitude of distortions across countries and the welfare gains from eliminating them.

5.1 Model

We employ a static open-economy version of the Long and Plosser (1983) multisector neoclassical growth model, similar to Jones (2013) . Each country c is a small open economy featuring J industries producing under conditions of perfect competition in output and input markets. Each firm in sector

j produces homogeneous output using the production function (suppressing country subscripts)

$$Y_j = A_j \cdot L_j^{\alpha_j} \left[\left(X_j^{\frac{\sigma-1}{\sigma}} + M_j^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \right]^{1-\alpha_j}, \tag{5.1}$$

$$X_j \equiv \prod_s X_{sj}^{\alpha_{sj}}, \ \sum_s \alpha_{sj} = 1, \tag{5.2}$$

where L_j is the labor input,[22] X_j is the domestic intermediate goods bundle, and M_j is the imported intermediate goods bundle for sector j.[23] Firms buy inputs subject to distortions or taxes τ_{sj} that are levied on domestic intermediate purchases from sector s. We assume that input-purchasing firms record the revenue from these distortions as value added (e.g. as profits or losses, or expenditures on primary inputs). This assumption implies that distortions generate observable variation in sectoral value-added shares and domestic intermediate shares across countries, despite the unit elasticity of substitution between labor and intermediate goods: see (5.4). This assumption is a natural one for many potential sources of distortions, such as costs of contract enforcement and monitoring, as well as explicit taxes and subsidies (since we measure inputs at basic prices and value added as the residual between gross output and intermediate inputs). Note that since the country is small in world markets, the quantities of foreign inputs that it imports does not affect import prices. This completes the description of the supply side of the model.

The demand side of the model is simple. Competitive firms combine the output from each sector into an aggregate final good

$$Y = \prod_j Q_j^{\beta_j}, \tag{5.3}$$

where Q_j is the quantity of the sector j good used in final demand. This bundle is consumed domestically and is also exported in order to pay for intermediate goods imports. For simplicity we assume that domestic consumers do not value foreign goods in consumption. Since the country is small in world markets, the quantity that it exports does not affect the export price, and hence there are no terms of trade effects.

We define a competitive equilibrium in the usual way, as a set of prices and allocations (of both goods and factors) such that all firms maximize profits taking prices as given, consumers maximize utility taking prices as given, workers choose their sector to maximize wage income, all goods and factor markets clear, and international trade is balanced. We assume that the revenue from the intermediate input distortions is a rebated lump sum to consumers. Since the competitive equilibrium allocation is efficient in the absence of distortions, any non-zero level of distortions induces misallocation that reduces welfare relative to the no-distortion equilibrium. It does not

[22]We can also think of L_j as a bundle of different primary factors, e.g. labor, land, capital, etc., assuming that these factors are used in the same proportions across industries and that they are all in fixed aggregate supply.

[23]Modeling substitution between domestic and foreign inputs as taking place at the level of the aggregate input bundles is driven by the fact that we only observe total intermediate imports for each domestic sector, not their sectoral composition.

follow, however, that any reduction in distortions short of eliminating them altogether necessarily generates a welfare improvement (Lipsey and Lancaster, 1956).

Appendix A contains a detailed derivation and discussion of the full equilibrium conditions of the model. Here we focus attention on the key condition that determines the observable entries in the input-output table. Manipulating the first order conditions of the firm, the observed share of total expenditure on inputs in sector j that is spent on domestic inputs from sector s, net of distortions, is given by

$$\lambda_{sj} = \frac{(1-\alpha_j)\alpha_{sj}}{1+\tau_{sj}} \cdot \frac{P_{j,X}^{1-\sigma}}{P_{j,X}^{1-\sigma} + P_{j,M}^{1-\sigma}}, \tag{5.4}$$

where

$$P_{j,X} = \prod_s \left(\frac{P_s(1+\tau_{sj})}{\alpha_{sj}} \right)^{\alpha_{sj}} \tag{5.5}$$

is the price index of domestic inputs bought by sector j, inclusive of distortions, and $P_{j,M}$ is the price of the imported input bundle in sector j. Equation (5.4) highlights the two channels through which distortions affect the observed domestic intermediate input shares. The first channel reflects the substitution between domestic intermediates and labor and is governed by the term $\frac{1}{1+\tau_{sj}}$. Larger distortions always reduce the observed domestic IO coefficient through this channel, due to our assumption that the direct costs of distortions are paid in labor. The second channel reflects the substitution between domestic and foreign intermediates and operates through the relative price terms in equation (5.4). Other factors that affect the relative price of domestic vs. foreign intermediates, such as changes in relative productivities, will also affect the domestic intermediate share through this substitution effect. In the empirically relevant case where $\sigma > 1$, higher domestic distortions will cause the share of domestic inputs relative to foreign inputs to decline as well.

We now briefly discuss the choices of unit elasticities of substitution between labor and the intermediate bundle, and between different sources of domestic intermediates, which are implicit in equations (5.1) and (5.2). Our interest is in long-run outcomes, and for this purpose, unit elasticities are a reasonable place to start.[24] Even more to the point, we lack the necessary data on relative sectoral prices (or productivity) to infer the size of domestic distortions with non-unit elasticities.

5.2 Identification of Technology and Distortions

Equation (5.4) shows that the observed IO shares reflect the effects of the technological factor shares (α_j and α_{sj}), distortions τ_{sj} and the relative prices of domestic and foreign intermediates. We now

[24]Measurement and statistical issues have impeded the formation of a strong consensus on elasticities of substitution between intermediate inputs and value added, or among various intermediate inputs. Broadly, the weight of the evidence seems to suggest that the elasticity of substitution between a capital-labor aggregate and intermediate inputs is somewhat lower than 1, but Cobb-Douglas typically cannot be rejected; see for example Atalay (2017); Peter and Ruane (2020). Within intermediate inputs, substitution patterns across sectors appear to be heterogeneous, with some elasticities exceeding 1 and some falling below (Peter and Ruane, 2020). Since most estimation strategies primarily utilize short-run time variation, the implications of existing empirical work for long-run elasticities are not completely clear.

discuss the identification of distortions from observed data on factor shares. By re-arranging the equation for the observed IO share (5.4) to solve for $1 + \tau_{sj}$ and substituting in the observed share of foreign intermediates in total input purchases f_j, we get

$$1 + \tau_{sj} = \frac{\alpha_{sj}(1 - \alpha_j - f_j)}{\lambda_{sj}} \tag{5.6}$$

Intuitively, the distortion that sector j faces when buying from s can be identified by comparing the predicted share of sector s inputs in a distortion-free environment, $\alpha_{sj}(1 - \alpha_j - f_j)$, with the actual observed share λ_{sj}. The smaller the observed domestic share λ_{sj} relative to that predicted by technology and foreign input prices (reflected in the observed import share f_j), the higher our estimated distortion for that sector.

It is easy to see from Equation (5.6) that when the observed IO coefficient λ_{sj} is small on average, small absolute cross-country differences in λ_{sj} will lead to large differences in the estimated distortions. The small size of many off-diagonal elements of the IO matrix (even at our high level of aggregation) combined with the presence of measurement error in the IO entries raises the concern that directly implementing Equation (5.6) may overstate the absolute magnitude of distortions. In practice, we assume a single distortion per selling sector, $\tau_{sj} = \tau_s,\ \forall j, s$, which is consistent with our findings in Tables 3, 4 and 5 that forward linkages tend to be correlated with output per worker at the sectoral level. We estimate τ_s by taking the λ_{sj} to the LHS of Equation (5.6), summing across buying sectors j, and then taking the term $\sum_j \lambda_{sj}$ back to the RHS to get

$$1 + \tau_s = \frac{\sum_j \alpha_{sj}(1 - \alpha_j - f_j)}{\sum_j \lambda_{sj}}. \tag{5.7}$$

This estimator weights each buying sector by the importance of sector s in its input bundle, and is therefore less sensitive to measurement error in small IO coefficients. The effect of this strategy on our computed gains from removing distortions tends to be conservative, i.e. to minimize gains.[25]

We next discuss our identification of the technology parameters α_j and α_{sj}. Identifying cross-country differences in technologies in the presence of distortions is challenging when technologies are allowed to vary arbitrarily across countries because technology differences and distortions affect the observed IO coefficients in similar ways (Jones, 2013).[26] Rather than direct attempt this challenging task, we take a "development accounting" approach in which we assume that technology differences across countries are limited or non-existent and identify them from data on economies that are

[25]As an additional measure to control the influence of measurement error, we cap our estimated distortions so that $\tau_s \leq 2.5, \forall s$. This cap is conservative with respect to the implied size of the gains, and affects a small number of observations, primarily in agriculture.

[26]Several recent papers take alternative approaches to identifying distortions arising from specific sources. Boehm (2022) and Boehm and Oberfield (2020) use micro data on the quality of contract enforcement to identify the impact of these distortions on input sourcing and assess the aggregate implications. Caliendo et al. (2017) employ a similar strategy to ours, but use time -series variation in observed input shares to identify changes in distortions relative to a base year using the World Input-Output Database.

assumed to be undistorted. Our baseline approach assumes that the U.S. economy is undistorted at any point in time. Under this assumption, α_j is the U.S. share of value added in sector j, $\alpha_{sj} = \frac{\lambda_{US,sj}}{1-\alpha_j - f_{US,j}}$ and the distortion in country c, selling sector s can be measured by

$$1 + \tau_{c,s} = \frac{\sum_j \frac{\lambda_{US,sj}}{1-\alpha_j - f_{US,j}} \cdot (1 - \alpha_j - f_{c,j})}{\sum_j \lambda_{c,sj}}. \tag{5.8}$$

As our data come from multiple time periods, we use the most temporally proximate U.S. IO table as the benchmark for each observation.

The assumption of identical technologies across all countries, while common and appealing in its simplicity, is strong. As a robustness exercise, we also implement a different procedure that assumes that a) technologies vary across countries, but similar countries employ similar technologies, and b) a sample of rich economies is undistorted. We then use the variation in input shares across rich countries to predict the technologies of poor countries based on "similar" rich countries in a regression framework. We discuss the method and the results in more detail in Appendix B. The main conclusion is that this alternative procedure results in gains from removing distortions that are of comparable order of magnitude but (on average) somewhat larger than those based on the U.S. technology assumption reported in the main text.

Our assumptions of identical technologies across countries and a single distortion for each selling sector, identified using equation (5.8), imply that equation (5.6) will generally not hold exactly for each country. Our baseline analysis assumes that these residuals reflect measurement error, and uses the fitted values from the identification procedure to conduct counterfactuals. An alternative assumption is that they reflect true, un-modeled differences in technologies. Appendix B reports the results using this alternative assumption, which are broadly similar to our baseline approach in the main text.

5.3 Counterfactual Analysis

Given data on observed domestic and foreign input shares for each country as well as the corresponding U.S. shares used to identify the common technologies, we use equation (5.8) to identify the sectoral input distortions $\tau_{c,s}$ for every economy in our sample. We combine this information with data on country-specific final demand shares and the value of imported inputs to conduct counterfactual analysis via the "hat algebra" approach that is commonly used in the quantitative trade literature. The "hat algebra" approach involves re-writing the equilibrium conditions in terms of initial data and the relative changes in endogenous variables across equilibria. The advantage of this approach is that it obviates the need to separately identify the initial relative sectoral productivities and relative sectoral output prices; indeed, these objects are not separately identified by our data. However, these objects are irrelevant for computing the welfare gains from removing some or all distortions from the economy (see Appendix A).

The remaining parameter to be calibrated is the elasticity of substitution σ between domestic and foreign inputs. This corresponds to the "macro" Armington elasticity which has been the subject of a large empirical literature in international trade, e.g. Imbs and Mejean (2015); Feenstra et al. (2018). We calibrate $\sigma = 2.5$ based on the recent meta-analysis of Bajzik et al. (2020), which aggregates over numerous studies and corrects for study quality and publication bias. Note that the conceptually appropriate elasticity for our exercise applies to the long run; the elasticity can be much smaller in the short run (Boehm et al., 2019). Our quantitative results are not very sensitive to reasonable alternative values for this parameter.[27]

5.4 Quantitative Results

We implement our approach to identifying distortions and computing the gains from removing them on our sample of market economies during the period 1965-2005. We omit 20 tables from earlier years because we lack a contemporaneous U.S. table with which to identify technologies,[28] leaving us with 172 country-year observations and 48 unique countries (excluding the U.S.). We compute the gains to each country (in each year) from eliminating all distortions, and from eliminating distortions in each selling sector separately while holding other distortions fixed.

Table 6: Summary Statistics: Distortions

	Mean	SD	Corr(y)	Time Trend
Agriculture	0.64	0.74	0.17	0.07
			(0.07)	(0.05)
Manufacturing	0.07	0.45	-0.43	0.02
			(0.08)	(0.01)
Services	0.28	0.39	-0.45	-0.17
			(0.07)	(0.03)
Mining, Cons. and Utilities	0.27	0.69	-0.40	-0.30
			(0.08)	(0.03)

Notes Statistics omit U.S. tables. Sample size is $N = 172$, with 48 unique countries. y is output per worker. The linear time trends are measured in decades and come from regressions with country fixed effects. Standard errors clustered at the country level.

Table 6 presents summary statistics for the identified distortions τ_s by the selling sector. Agriculture faces the largest average distortion when selling inputs to other sectors as well as the largest variation across countries. This may not be surprising in light of pervasive market failures in developing countries and heavy state involvement in the agricultural sector for rich economies. It also dovetails nicely with the fact that cross-country variation in TFP is highest in agriculture (Restuccia

[27]Gains tend to be lower for higher values of σ, since increased substitutability betweeen domestic and foreign inputs lowers the cost of domestic distortions.

[28]Our earliest U.S. table is from 1972. If we apply the 1972 U.S. technology to the pre-1965 tables, both rich and poor countries appear to be highly distorted in those years.

and Rogerson, 2008). Interestingly, distortions in Agriculture are modestly positively correlated with income per capita and do not display a strong systematic time trend.

Mean distortions are also high in Services and Mining, Construction and Utilities, and fairly low in Manufacturing. However, the cross-country variation in distortions in Manufacturing is relatively high, suggesting that many countries are on net subsidizing manufacturing inputs (a distortion that also generates welfare losses). Distortions in these three sectors all display strong negative correlations with output per worker, which suggests that distortions in these sectors have the most potential for explaining cross-country income differences. Distortions in Manufacturing display no strong time trend, while distortions in Services and Mining, Construction, and Utilities display strong negative time trends.[29]

Table 7: Summary Statistics: Welfare Gains from Eliminating Distortions

	Mean	SD	Median	90^{th} Pctile	Time Trend
Aggregate	6.85%	7.79%	5.31%	12.27%	-1.18%
					(0.42)
Agriculture	0.86%	1.82%	0.34%	2.38%	-0.40%
					(0.14)
Manufacturing	1.90%	5.16%	0.35%	3.79%	0.08%
					(0.19)
Services	2.26%	2.90%	1.10%	7.05%	-0.97%
					(0.31)
Mining, Cons. and Utilities	1.22%	1.63%	0.39%	3.94%	0.10%
					(0.45)

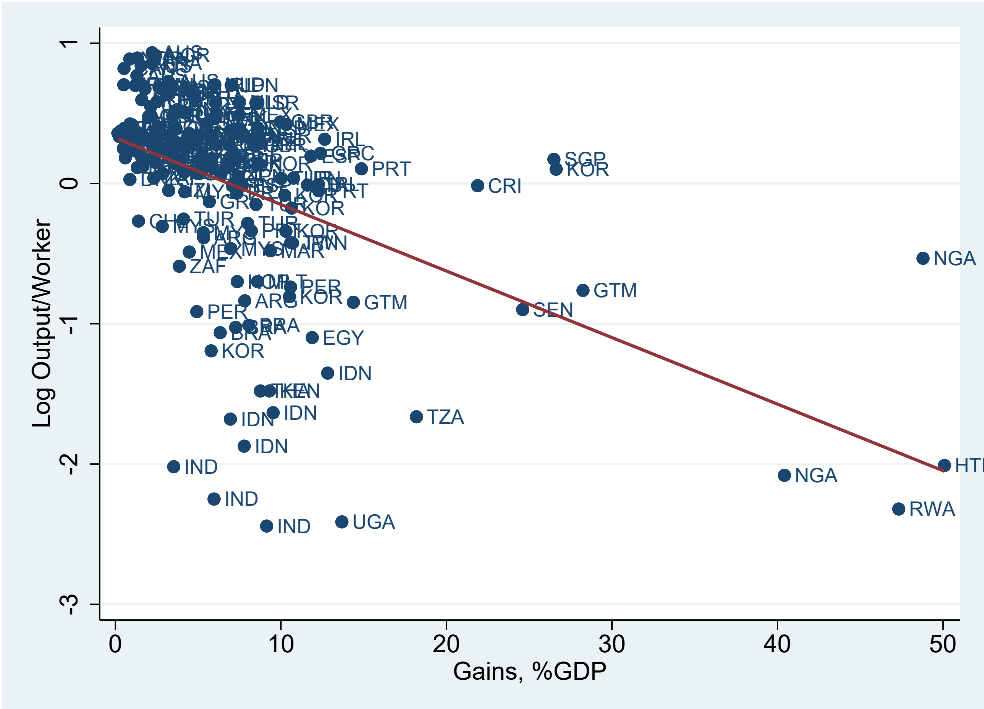
Notes Statistics omit U.S. tables. Sample size is $N = 179$, with 48 unique countries. y is output per worker. The linear time trends are measured in decades and come from regressions with country fixed effects. Standard errors clustered at the country level.

Table 7 summarizes the main results on the welfare gains from eliminating distortions, entirely and sector-by-sector. The mean welfare gain from eliminating all distortions is 6.85% of initial income per capita, with a standard deviation of 7.79%. The distribution of gains is skewed to the right; while a large number of countries gain only modestly from eliminating distortions, a minority of highly distorted countries have a substantial gain of 12% or more. The average gains within countries tend to fall over time, although the time trend is not estimated very precisely. This finding makes sense in light of both the modest downward trend in distortions over time and increasing trade in intermediate inputs, which moderates the negative effect of domestic input distortions.

Turning to the sector-level results, we find that the largest average gains come from eliminating distortions in the service sector. This reflects the fact that the service sector tends to be large and have strong domestic linkages with the rest of the economy (see Table 2), as well as a fairly high average level of distortions. Despite having the highest average level of distortions, the gains in Agriculture

[29]Both the estimated correlations with output per worker and the time trends are robust to using the absolute value of τ_s rather than the numerical value.

Figure 2: Aggregate Gains and Log Output/Worker



Notes: Log Output/Worker is de-meaned by time. Gains are not de-meaned.

tend to be small due to its weak linkages with the rest of the economy. The case of manufacturing is interesting because despite having low average distortions, the gains from eliminating them are nearly as large as those in Services and the variation across countries is the largest of any sector. The strong domestic forward linkages that are characteristic of the manufacturing sector strongly amplify the welfare effects of even modest distortions, consistent with the theoretical results of Liu (2019).

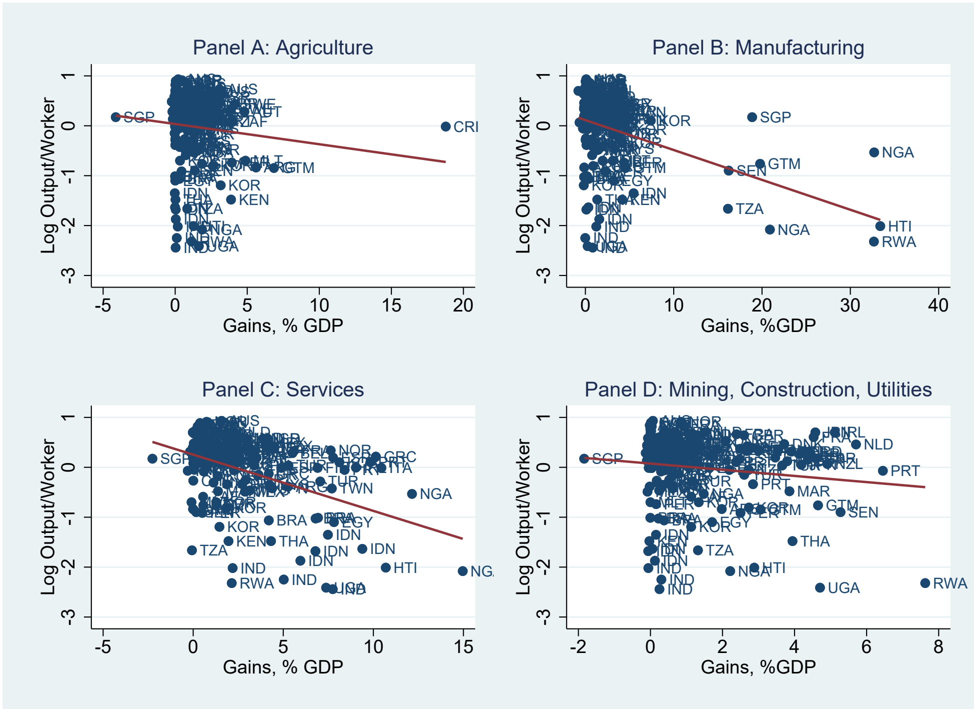
Figure 2 plots the relationship between the aggregate gains and log output per worker, demeaned by time period. There is a strong negative relationship between gains and aggregate productivity, with a least squares slope coefficient of -0.05 and standard error of 0.01.[30] Most countries enjoy gains of under 20% from eliminating distortions, but a small number of mostly poor countries have much larger gains of up to 50%. There is much more cross-country variation in gains at lower income levels. Figure 3 plots the relationship between the gains from eliminating distortions in each sector separately and log output per worker. Gains from eliminating distortions in Agriculture and Mining, Construction, and Utilities are only weakly correlated with log output per worker, whereas the gains in Manufacturing and Services are strongly negatively correlated with log output per worker.[31] The manufacturing sector also has the most extreme gains, and the countries that achieve them are by and large the same countries with large aggregate gains.

Our main results regarding the gains from eliminating distortions are robust to treating the

[30] Despite the obvious presence of outliers, they are not very influential in the estimation. Both median regression and robust regression deliver similar results.

[31] This conclusion is also robust to methods that minimize the influence of outliers.

Figure 3: Sectoral Gains and Log Output/Worker



Notes: Log Output/Worker is de-meaned by time. Gains are not de-meaned.

residuals from the estimation procedure as true variation in technologies, rather than as measurement error as in the main text. They are also robust to an alternative identification strategy that identifies technology and distortions by matching poor countries to "similar" rich countries rather than just the United States. Both of these alternative procedures deliver somewhat higher gains than our baseline. A fuller description of the methods and results is available in Appendix B.

Our results imply sizable welfare gains from eliminating distortions, especially in the manufacturing and service sectors. Poor countries tend to gain more from eliminating distortions, and hence the presence of distortions can help to partially explain cross-country variations in productivity and living standards. However, distortions in IO linkages can explain only a modest fraction of the observed dispersion in aggregate productivity.

5.5 Comparing model and data

We now investigate the extent to which our calibrated model and our approach to identifying distortions is consistent with the empirical relationships between aggregate productivity and IO linkages that we found in Section 4. Recall that our regression analysis showed a strong positive correlation between log output per worker and the AOM, as well as some of its components (Table 5). This analysis did not establish a causal relationship between distortions and productivity; omitted variables that are correlated with the AOM could also be driving the observed correlation in the data. In contrast, the correlation between the (negative) gains from eliminating distortions implied by our model and the observed AOM does reflect a causal relationship between distortions and productivity, albeit not an exact one since the AOM is not a sufficient statistic for the welfare costs of distortions. It is therefore interesting to compare the two correlations to see if they line up with each other.

Table 8: AOM and Gains from Eliminating Distortions

	(Negative) Log Gains			
	Panel A: AOM			
AOM	0.45	0.60	0.20	0.22
	(0.15)	(0.20)	(0.08)	(0.09)
Imported Inputs Share		0.27		0.09
		(0.17)		(0.08)
R^2	0.20	0.25	0.04	0.05
	Panel B: Forward Linkages			
Agriculture	0.04	0.17	0.15	-0.19
	(0.10)	(0.11)	(0.10)	(0.11)
Manufacturing	0.20	0.28	0.03	0.04
	(0.15)	(0.18)	(0.17)	(0.87)
Services	0.37	0.48	0.25	0.28
	(0.11)	(0.13)	(0.17)	(0.18)
Mining, Cons. and Utilities	0.10	0.09	0.00	0.01
	(0.08)	(0.08)	(0.09)	(0.08)
Imported Inputs Share		0.31		0.14
		(0.16)		(0.10)
R^2	0.24	0.29	0.07	0.09
Number of Observations	186	186	167	167
Country FE	No	No	Yes	Yes

Notes Standardized coefficients from residualized regressions, controlling for time FE and imported inputs (plus country FE in columns (3) and (4). Panel B is the same specification as in Panel A, except that the coefficients on the separate row sums comprising the AOM are allowed to vary across sectors.

Concretely, we take the (negative) log welfare gains from removing distortions according to our model and regress them on the observed data on the AOM and import shares, residualizing and standardizing the coefficients exactly as we did in the specifications reported in Table 5. Panel A of Table 8 reports the results of this exercise. Strikingly, the standardized coefficients are very close to those obtained in our cross-country and panel regressions reported in Panel A of Table 5. The fit between the model and data remains strong as we disaggregate AOM into forward linkages by sector in the cross-section (Panel B), but does weaken somewhat in the panel specifications. Taken together, these results suggest that our model does well at capturing the positive relationship between AOM and output per worker observed in the data both qualitatively and quantitatively.[32]

[32]The coefficients in Tables 5 and 8 are standardized. The interpretation is that a standard deviation difference in AOM is associated with similar increases in log output per worker (Table 5) and (negative) log welfare gains (Table 8) in terms of standard deviations. However, the variation in cross-country income differences is much higher than the variation in the gains from removing distortions. Thus approximate equality of the standardized coefficients implies that the ratio of the

6. Conclusion

This paper has documented the basic systematic empirical relationships between input-output linkages and economic development, both across countries and over time, using the most extensive centralized digitized collection of IO tables available. There is a strong positive correlation between the strength of domestic IO linkages and output per worker, driven primarily by forward linkages in the manufacturing and service sectors. We develop a quantitative model in which cross-country differences in IO coefficients are driven by distortions and take the model to the data. Our results imply that distortions in the allocation of intermediate goods are quantitatively significant determinants of cross-country income differences, with the largest contribution coming from the service sector.

In recent years there has been an explosion of research into input-output networks, much of it utilizing highly detailed microeconomic data from a few countries. Our comparative macroeconomic and time-series approach to data and analysis provides a complementary perspective to this rapidly growing field.

un-standardized coefficients is approximately equal to the ratio of the standard deviations of log output per worker and the welfare gains from removing distortions. This in turn implies that the gains from eliminating distortions are very highly correlated with other sources of cross-country income differences.

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A. Theoretical Appendix

A.1 Derivation of the Equilibrium Conditions

Firms in sector j solve

$$\max \; P_j Y_j - w L_j - \sum_s (1+\tau_{sj}) P_s X_{sj} - P_j^M M_j. \tag{A.1}$$

The first order conditions for optimization with respect to each input yield the following equations:

$$\alpha_j P_j Y_j = w L_j, \tag{A.2}$$

$$(1-\alpha_j)\alpha_{sj} \frac{X_j^{\frac{\sigma-1}{\sigma}}}{\left(X_j^{\frac{\sigma-1}{\sigma}} + M_j^{\frac{\sigma-1}{\sigma}}\right)} P_j Y_j = (1+\tau_{sj}) P_s X_{sj}, \tag{A.3}$$

$$(1-\alpha_j) \frac{M_j^{\frac{\sigma-1}{\sigma}}}{\left(X_j^{\frac{\sigma-1}{\sigma}} + M_j^{\frac{\sigma-1}{\sigma}}\right)} P_j Y_j = P_j^M M_j. \tag{A.4}$$

The fact that firms in sector j earn zero profits implies that

$$P_j = \frac{1}{A_j}\left(\frac{w}{\alpha_j}\right)^{\alpha_j}\left(\frac{P_{j,I}}{1-\alpha_j}\right)^{1-\alpha_j}, \tag{A.5}$$

where $P_{j,I}$ is the price index for intermediate inputs bought by firms in sector j, given by

$$P_{j,I} = \left(P_{j,X}^{1-\sigma} + P_{j,M}^{1-\sigma}\right)^{\frac{1}{1-\sigma}}, \tag{A.6}$$

with $P_{j,M}$ being the price of imported inputs for buying sector j and $P_{j,X}$ the price index of the domestic intermediate goods bundle for buying sector j, which is given by

$$P_{j,X} = \prod_s \left(\frac{P_s(1+\tau_{sj})}{\alpha_{sj}}\right)^{\alpha_{sj}}. \tag{A.7}$$

The final goods firm sells $Y = \prod_j Q_j^{\beta_j}$ at given price $\mathbb{P}$ (which is pinned down by foreign demand), which we normalize $\mathbb{P} = 1$. With this normalization, the final goods firm has sectoral demands satisfying

$$\beta_j = \frac{P_j Q_j}{Y}. \tag{A.8}$$

It makes zero profits when

$$1 = \prod_j \left(\frac{P_j}{\beta_j}\right)^{\beta_j} \tag{A.9}$$

Consumers have incomes

$$E = w\bar{L} + \sum_j \sum_s \tau_{sj} P_s X_{sj} \tag{A.10}$$

where $\bar{L}$ is the total labor endowment. Consumers spend all income on the domestic consumption good. International trade balance implies that

$$Y - E = \sum_j P_{j,M} M_j. \tag{A.11}$$

Finally, labor market clearing implies that

$$\sum_j L_j = \bar{L}. \tag{A.12}$$

It will be useful later to develop some input-output algebra relating aggregate final demand Y to the demand for labor in each sector, given some level of prices and wages. For firms in sector s, we have that total sales equals final sales plus intermediate sales. Using the first order conditions above, we can express this goods market clearing condition as

$$P_s Y_s = \beta_s Y + \sum_s \lambda_{sj} P_j Y_j, \tag{A.13}$$

where λ_{sj} is the share of total input expenditure in sector j that is spent on domestic inputs from sector s, net of distortions (i.e. the observed input-output share). Again manipulating the first order conditions, we have that

$$\lambda_{sj} = \frac{(1-\alpha_j)\alpha_{sj}}{1+\tau_{sj}} \cdot \left(\frac{P_{j,X}}{P_{j,I}}\right)^{1-\sigma}. \tag{A.14}$$

Note that λ_{sj} is a function of domestic and foreign input prices, distortions and technology. Now, letting the matrix $\Lambda \equiv \{\lambda_{sj}\}$, we define the vector of Domar weights as

$$\theta \equiv (I - \Lambda)^{-1} \beta, \tag{A.15}$$

which satisfies

$$P_s Y_s = \theta_s Y. \tag{A.16}$$

The Domar weight of sector s is the ratio of total sales in sector s to total final demand. Note that it depends only on domestic and foreign input prices, distortions and technology.

We can express the necessary and sufficient conditions for equilibrium more compactly as a set of wages, output prices and labor allocations that satisfy the following conditions:

1. Wages w and domestic output prices P_j solve the zero profit conditions for each sector,

$$P_j = \frac{1}{A_j}\left(\frac{w}{\alpha_j}\right)^{\alpha_j}\left(\frac{P_{j,I}}{1-\alpha_j}\right)^{1-\alpha_j}, \forall j \in J, \tag{A.17}$$

   as well as the zero profit condition for the final goods sector

$$1 = \prod_j \left(\frac{P_j}{\beta_j}\right)^{\beta_j}. \tag{A.18}$$

   This is a system of $J+1$ equations in $J+1$ unknowns with a unique solution for mild regularity conditions.

2. Given domestic output prices P_j and wages w, and given a level of aggregate final demand Y, the demand for labor in sector j is given by

$$L_j = \alpha_j \theta_j \frac{Y}{w}. \tag{A.19}$$

3. Given wages and prices, aggregate final demand Y must be such that labor demand equals labor supply:

$$\bar{L} = \sum_j \alpha_j \theta_j \frac{Y}{w} \quad \Rightarrow \quad Y = \frac{w\bar{L}}{\sum_j \alpha_j \theta_j}. \tag{A.20}$$

All other equilibrium objects can be easily computed using the solution to this system and simple algebra. It is also easy to see that, by substituting (3) into (2), we solve for the labor allocations in each sector directly as a function of the Domar weights. Solving the system of equations (A.17) and (A.18) involves finding the fixed point of a non-linear function. Once that has been accomplished, the rest of the equilibrium system can be solved with linear algebra.

A.2 Hat Algebra for Counterfactual Analysis

We consider a counterfactual change in the distortion τ_{sj} and compute the new equilibrium. Let $\hat{x} = x'/x$, where x is a variable observed at the initial equilibrium and x' is the same variable observed in the counterfactual equilbrium. Then the solution for the new endogenous variables $\{\hat{P}_j, \hat{L}_j\}$ satisfy the following system of equations:

$$\hat{P}_j = \hat{w}^{\alpha_j}\left(\Psi_j \prod_s \left(\hat{P}_s \widehat{(1+\tau_{sj})}\right)^{\alpha_{sj}(1-\sigma)} + (1-\Psi_j)\right)^{\frac{1-\alpha_j}{1-\sigma}},$$

$$1 = \prod_j \hat{P}_j^{\beta_j},$$

$$\hat{L}_j = \hat{\theta}_j \cdot \frac{\sum_s \alpha_s \theta_s}{\sum_s \alpha_s \theta_k \hat{\theta}_k},$$

$$\hat{\theta}_j \theta_j = \beta_j + \sum_k \lambda_{sj}\theta_s \cdot \hat{\lambda}_{sj}\hat{\theta}_s,$$

$$\hat{\lambda}_{sj} = \frac{1}{\widehat{1+\tau_{sj}}} \cdot \frac{\prod_k (\hat{P}_k \widehat{(1+\tau_{kj})})^{\alpha_{kj}(1-\sigma)}}{\Psi_j \prod_k (\hat{P}_k \widehat{(1+\tau_{kj})})^{\alpha_{kj}(1-\sigma)} + 1 - \Psi_j},$$

where $\Psi_j = \frac{1-\alpha_j - f_j}{1-\alpha_j}$ and $f_j \equiv P_{j,M}M_j / P_j Y_j$. Once the first two equations are solved numerically, the other equations can be solved using linear algebra.

All other endogenous variables can be easily computed once this system is solved. In particular, the hat welfare change is given by

$$\hat{E} = \hat{Y}\left(\frac{Y}{E} - \sum_j \frac{P_{j,M}M_j}{E} \cdot \frac{1-\Psi_j\hat{\Psi}_j}{1-\Psi_j}\hat{\theta}_j\right), \tag{A.21}$$

where

$$\hat{\Psi}_j = \widehat{1+\tau_{sj}} \cdot \hat{\lambda}_{sj}, \tag{A.22}$$

for any s and $E = Y - \sum_j P_{j,M}M_j$

The data requirements for computing the counterfactual changes are the following:

1. The true technology parameters α_j and α_{sj}
2. Final demand shares β_j
3. The initial level of distortions τ_{sj}
4. The observed shares of inputs purchased by sector j from domestic sources (λ_{sj}, used to compute the initial Domar weights) and foreign sources (f_j).

5. The initial ratio of final demand Y to E (the latter being computed as final demand less the value of imported inputs, $\sum_j P_{j,M} M_j$) and the value of imported inputs in sector j relative to consumption expenditures E.

B. Empirical Appendix

B.1 Aggregation

As described in Section 3, we standardize the heterogenous sectoral classifications found in the original data sources by aggregating into four sectors: Agriculture, Manufacturing, Services and a residual sector comprising Mining, Construction and Utilities (MCU). Consistent classification allows us to compare individual IO coefficients across countries and over time, as well as aggregate statistics such as the AOM. Consistent aggregation guards against the possibility that systematic differences in sectoral classifications are correlated with output per worker, as would be the case if richer countries systematically reported IO tables at a more disaggregated level. The cost of ensuring consistent aggregation is the loss of some of the rich sectoral detail available for many tables.

Figure A1: AOM with and without aggregation

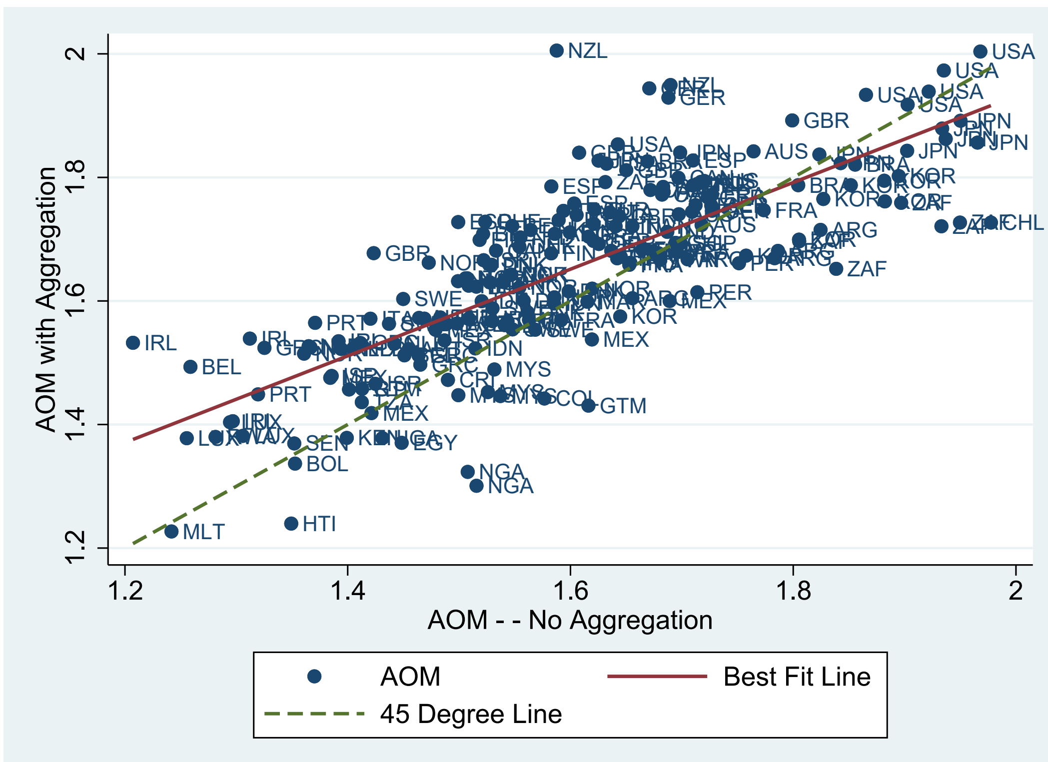
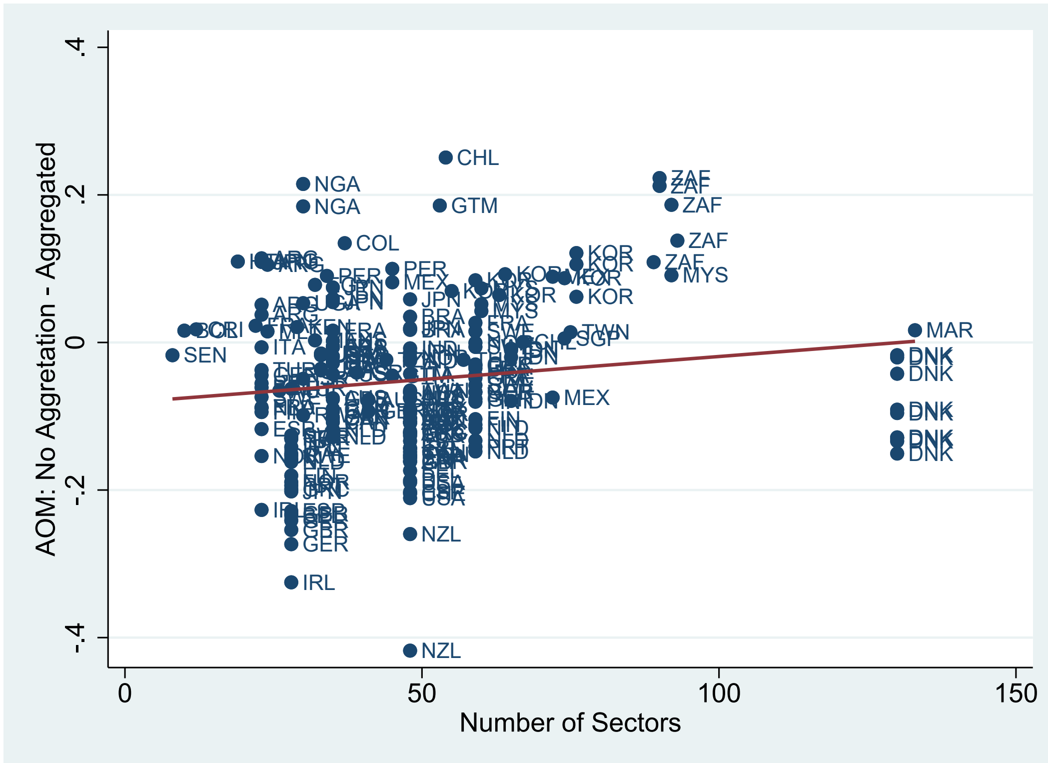


Figure A1 plots the AOM computed using the consistently aggregated $4x4$ IO matrices on the vertical axis against the AOM computed using the original IO tables on the horizontal axis. The two measures are highly positively correlated, with an $R^2 = 0.60$, suggesting that our relatively coarse aggregation preserves much of the information in the original tables. However, there is a noticeable tendency for aggregation to raise the computed AOM of countries with low or medium disaggregated AOM relative to those with high disaggregated AOM, as can be inferred from the fact that the slope of the best fit line is less than 1 (0.70, with a standard error of 0.06). Our consistent aggregation is designed precisely to neutralize any effect of these systematic differences on our empirical results.

Figure A2: Difference without & with aggregation vs. Number of Sectors



We next ask whether the number of sectors in the original table's classification can explain the observed differences between the AOM with and without aggregation. Figure A2 plots this difference against the number of sectors in the original table. We see a slight tendency for a finer sectoral classification to be associated with higher values of AOM computed without aggregation, relative to AOM with aggregation. However, the explanatory power of this regression is limited; the coefficient is 0.0005 with a standard error of 0.0003, and the $R^2 = 0.02$.

B.2 Centrally Planned Economies

In this section we compare the IO tables of countries with a history of central planning to those from market economies. The countries that both a) had IO table and real GDP data both available and b) were coded as having a history of central planning are China, the Czech Republic, Estonia, Hungary, Lithuania, Latvia, Macedonia, Poland, Romania, Russia, the Slovak Republic and Slovenia. We did not obtain usable IO tables from most other countries with a history of central planning; occasionally we have IO tables for countries (or former countries) but no real GDP data (e.g. the former Yugoslavia). As noted in the main text, it is unclear in theory how to compare IO tables constructed from transactions at market prices to those from non-market economies. Here, we document that emprically countries with a history of central planning exhibit striking systematic differences in linkage measures compared to market economies, both in levels and in correlations with output per worker.

Table A1: IO Coefficients: Means and Standard Deviations for Centrally Planned Economies

		Using Sector			
		Agriculture	Manufacturing	Services	Min., Con. & Utilities
Producing Sector	Agriculture	0.21	0.06	0.01	0.01
		(0.06)	(0.03)	(0.01)	(0.01)
	Manufacturing	0.12	0.21	0.09	0.17
		(0.05)	(0.10)	(0.05)	(0.08)
	Services	0.10	0.12	0.22	0.14
		(.04)	(.03)	(.05)	(.02)
	Min., Con. & Utilities	0.02	0.05	0.04	0.17
		(0.01)	(0.02)	(0.01)	(0.09)
	Imported Inputs	0.08	0.27	0.07	0.13
		(0.04)	(0.13)	(0.04)	(0.06)
	Total Domestic Share	0.45	0.43	0.36	0.48
		(0.07)	(0.11)	(0.06)	(0.08)
	Total Intermediate Share	0.53	0.71	0.43	0.61
		(0.07)	(0.08)	(0.06)	(0.06)

Notes Unweighted averages calculated separately for each coefficient, across $N = 29$ country-year observations.

Table A1 shows the means and standard deviations of the individual IO coefficients from the sample of countries with a history of central planning. This table should be compared to the identical statistics calculated from the main sample (Table 2 in the main text); statistics that are substantially higher those reported in Table 2 are highlighted in red. Countries with a history of central planning exhibit substantially higher intermediate input shares of gross output in all sectors, with most sectors exhibiting much higher shares of domestic intermediates as well (manufacturing being the exception).

Most of these differences are not attributable to larger individual entries of the IO table, but rather to systematically higher values of most entries.

Figure A3: AOM and Log Output/Worker, including formerly centrally planned economies

Notes Standardized coefficients from residualized regressions, controlling for time FE and imported inputs in Panel A, adding country FE in panel B.

Figure A3 redoes the analysis underlying Figure 1 in the main text, but includes the economies with a history of central planning (denoted by orange triangles) and allows the relationship between log output per worker and the AOM to have a different slope (the orange dashed line). In the cross-section (Panel A), we observe that most historically planned economies have much higher AOM than even most rich countries, but are themselves only middle income on average. Within the sample of historically planned economies, higher AOM is weakly associated with lower output per worker. In the time series (Panel B), we first observe that the *range* of changes over time in the AOM is much larger for countries with a history of central planning than for market economies. Second, these changes are if anything negatively associated with changes in output per worker. The story behind the figure is that we observe a number of IO tables for Eastern European countries in the 1960s and 1970s, which exhibit very high meausured AOM. We also have a number of observations from the late 1990s or early 2000s, during the long transition from a planned to a market economy. The almost univeral pattern is that AOM falls dramatically during the transition, while output (relative to global trends) is roughly flat or slighly higher at the time of measurement.[33]

[33]The post-communist countries almost universally experienced deep contractions immediately following the collapse of communism. By the late 1990s or early 2000s, output had largely recovered or exceeded its previous peak.

B.3 Alternative Measures of IO Linkages

Table A2: AOM and Log Output/Worker, Alternative Measures

	Log Output/Worker			
	Panel A: AOM			
AOM	0.35	0.56	0.17	0.22
	(0.11)	(0.12)	(0.08)	(0.08)
Imported Inputs Share		0.40		0.19
		(0.11)		(0.12)
	Panel B: WAOM			
WAOM	0.14	0.25	0.15	0.16
	(0.11)	(0.13)	(0.13)	(0.12)
Imported Inputs Share		0.23		0.15
		(0.12)		(0.13)
	Panel C: MDL			
MDL	0.41	0.62	0.20	0.24
	(0.10)	(0.10)	(0.09)	(0.09)
Imported Inputs Share		0.42		0.19
		(0.11)		(0.12)
	Panel D: MDL w/ Imported Inputs			
MDL w/ Imp	0.57		0.24	
	(0.10)		(0.11)	
Number of Observations	199	199	179	179
Country FE	No	No	Yes	Yes

Notes Standardized coefficients from residualized regressions, controlling for time FE and imported inputs (plus country FE in columns (3) and (4).

Table A2 reports the results of regressions of the same form as those in Table 5 in the main text, but using different aggregate linkage measures. The alternative measures $WAOM$ and MDL are defined in Section 2. The measure "MDL w/IMP" is equal to the $MDL + \frac{1}{N}\sum_n importshare_n$, where $importshare_n$ is the share of imported inputs in total output in sector n. It treats imported inputs symmetrically with domestic inputs.

B.4 Alternative Counterfactuals

In this section we report some results on the robustness of our counterfactual analysis to alternative identification assumptions to those used in the main text. The assumption of common technologies across all countries, while standard in the literature and appealing in its simplicity, is fairly strong. As an alternative, we implement an alternative identification scheme that assumes that a) technologies vary across countries, but similar countries employ similar technologies, and b) a sample of rich economies are undistorted. Concretely, we fit a multiplicative model of technologies to the rich country sample, where rich countries are defined as having 75% of U.S. output per worker in any year (note the definition is time invariant). The model is

$$\ln a_{j,c} = \beta_{0,sj} + \beta_{1,sj} \ln(population_c) + \varepsilon_{sj,c}, \tag{B.1}$$

where $a_{sj,c}$ is the s,j IO coefficient for country c. We use a similar model for the value-added shares. We estimate the models via equation-by-equation OLS and use the fitted values to predict technologies out of sample for the poor countries, making sure to rescale each countries technology so that the factor shares sum to 1. We then conduct our counterfactual analysis on the gains from removing distortions on the sample of poor countries.

Table A3 reports a summary of the results. These results should not be compared directly to those in Table 7 in the main text, because the underlying sample in Table 7 includes both rich and poor countries while the sample in Table A3 includes only poor countries. Instead they should be compared to the results using the U.S. technology identication assumption from the main text, but restricted to the same sample of poor countries only, which we report below in Table A4.

A comparison of Tables A3 and A4 shows that our baseline assumption of common technologies across countries (with the U.S. undistorted) generates lower gains ($\approx$ 11.4%) on average than the alternative identification strategy that uses comparable rich countries as the reference ($\approx$ 15.5%). These differences seem to be mostly accounted for by the much higher average gains from removing distortions in the Mining, Construction and Utilities sector under the alternative assumption ($\approx$ 7.4% vs $\approx$ 1.4%).

Table A3: Welfare Gains from Eliminating Distortions, Rich Country Technology

	Mean	SD	Median	90^{th} Pctile
Aggregate	15.63%	10.32%	13.11%	30.62%
Agriculture	3.86%	2.70%	3.13%	7.75%
Manufacturing	2.19%	5.19%	0.21%	6.90%
Services	1.99%	2.53%	1.05%	4.77%
Mining, Cons. and Utilities	7.35%	4.32%	7.74%	12.96%

Notes Sample size is $N = 61$.

Table A4: Welfare Gains from Eliminating Distortions, US Technology Poor Countries Only

	Mean	SD	Median	90^{th} Pctile
Aggregate	11.37%	11.01%	8.06%	24.61%
Agriculture	1.56%	2.67%	0.84%	3.88%
Manufacturing	4.08%	8.03%	1.10%	16.14%
Services	3.62%	3.59%	2.19%	8.41%
Mining, Cons. and Utilities	1.44%	1.79%	0.54%	3.94%

Notes Same sample as in Table A3.

We next investigate the quantitative implications of our treatment of the residuals in our estimation procedure. Our assumption of a single distortion per selling sector along with our assumption of common technologies across countries together imply that our estimation procedure will generate residuals in the country-specific intermediate shares (see equations (5.6) and (5.8)). Our baseline analysis assigns these residuals to measurement error, and uses the fitted values from the identification procedure to conduct the counterfactuals. An alternative assumption is that these residuals reflect true, unmodeled differences in technologies. Under this alternative assumption, we would use the observed shares in the data to conduct the counterfactuals.

Table A5: Welfare Gains from Eliminating Distortions, Residuals Assigned to Technology

	Mean	SD	Median	90^{th} Pctile	Time Trend
Aggregate	8.67%	9.69%	6.31%	14.50%	-1.63%
					(0.62)
Agriculture	1.57%	2.92%	0.53%	4.63%	-0.73%
					(0.38)
Manufacturing	2.00%	6.72%	0.22%	4.17%	0.23%
					(0.21)
Services	2.90%	3.94%	1.09%	8.46%	-1.07%
					(0.36)
Mining, Cons. and Utilities	1.28%	1.60%	0.47%	3.88%	-0.07%
					(0.23)

Notes Statistics omit U.S. tables. Sample size is $N = 179$, with 48 unique countries (same as Table 7 in the main text). y is output per worker. The linear time trends are measured in decades and come from regressions with country fixed effects. Standard errors clustered at the country level.

Table A5 summarizes the gains calculations implied by assigning the residuals to technology differences (compare to Table 7 in the main text). The results are broadly similar, with slightly higher average gains found under this alternative specification ($\approx 8.7\%$ vs $\approx 6.9\%$).

C. Data Appendix

Table A6: Quality Index and Explanation

Quality Rating	Explanation
1	No known outstanding issues.
2	Issue discovered in original source (e.g. violation of adding up constraints). Solution proposed but cannot be checked.
3	Only total inputs, not domestic separately (or cannot tell).
4	Trade and transportation margins reported, not treated as sectors. May also list only total inputs (not domestic).
5	Major errors, omitted sectors, etc.

Table A7: Data Sources for IO Tables

Country	Years	Source	Quality Index
Argentina	1950, 1953, 1959, 1963, 1970	United Nations Economic Commission for Latin America, Tablas de insumo-producto en América Latina, Santiago de Chile: Naciones Unidas, 1983	1
Argentina	1997	OECD, rev. 3	1
Australia	1968, 1974, 1986, 1989	OECD, rev. 1	1
Australia	1994	OECD, rev. 2	1
Australia	1998	OECD, rev. 3	1
Austria	1961, 1964	Economic Commission for Europe, Standardized input-output tables of ECE countries ..., New York: United Nations, various years	3
Austria	1976	Economic Commission for Europe, Standardized input-output tables of ECE countries for the years around 1975, New York: United Nations, 1982	1
Austria	1995, 2000, 2004	OECD, rev. 3	1
Burundi	1970	UNIDO, Input-output tables for developing countries, New York: United Nations, 1985	1
Belgium	1959	Economic Commission for Europe, Standardized input-output tables of ECE countries for the years around 1959, New York: United Nations, 1972	5
Belgium	1965, 1970	Economic Commission for Europe, Standardized input-output tables of ECE countries ..., New York: United Nations, various years	1
Belgium	1995, 2000, 2004	OECD, rev. 3	1

Bangladesh	1962	UNIDO, Input-output tables for developing countries, New York: United Nations, 1985	3
Bulgaria	1963	Economic Commission for Europe, Standardized input-output tables of ECE countries for the years around 1959, New York: United Nations, 1972	1
Bolivia	1958	United Nations Economic Commission for Latin America, Tablas de insumo-producto en América Latina, Santiago de Chile: Naciones Unidas, 1983	1
Brazil	1959	United Nations Economic Commission for Latin America, Tablas de insumo-producto en América Latina, Santiago de Chile: Naciones Unidas, 1983	3
Brazil	1970	United Nations Economic Commission for Latin America, Tablas de insumo-producto en América Latina, Santiago de Chile: Naciones Unidas, 1983	5
Brazil	1995, 2000, 2005	OECD, rev. 3	1
Canada	1965, 1975	Economic Commission for Europe, Standardized input-output tables of ECE countries ..., New York: United Nations, various years	3
Canada	1971	Economic Commission for Europe, Standardized input-output tables of ECE countries for the years around 1975, New York: United Nations, 1982	3
Canada	1981, 1986, 1990	OECD, rev. 1	1
Canada	1995, 2000	OECD, rev. 3	1
Switzerland	2001	OECD, rev. 3	1
Chile	1962	United Nations Economic Commission for Latin America, Tablas de insumo-producto en América Latina, Santiago de Chile: Naciones Unidas, 1983	1
Chile	1977	UNIDO, Input-output tables for developing countries, New York: United Nations, 1985	1
Chile	1986	http://www.bcentral.cl	2
Chile	1996	http://www.bcentral.cl	1
China	1995, 2000, 2005	OECD, rev. 3	1
Ivory Coast	1976	UNIDO, Input-output tables for developing countries, New York: United Nations, 1985	4
Colombia	1953	United Nations Economic Commission for Latin America, Tablas de insumo-producto en América Latina, Santiago de Chile: Naciones Unidas, 1983	5
Colombia	1956	United Nations Economic Commission for Latin America, Tablas de insumo-producto en América Latina, Santiago de Chile: Naciones Unidas, 1983	1

Colombia	1960	United Nations Economic Commission for Latin America, Tablas de insumo-producto en América Latina, Santiago de Chile: Naciones Unidas, 1983	5
Colombia	1970	United Nations Economic Commission for Latin America, Tablas de insumo-producto en América Latina, Santiago de Chile: Naciones Unidas, 1983	3
Costa Rica	1957	United Nations Economic Commission for Latin America, Tablas de insumo-producto en América Latina, Santiago de Chile: Naciones Unidas, 1983	5
Costa Rica	1972	United Nations Economic Commission for Latin America, Tablas de insumo-producto en América Latina, Santiago de Chile: Naciones Unidas, 1983	1
Czechoslovakia	1962	Economic Commission for Europe, Standardized input-output tables of ECE countries for the years around 1959, New York: United Nations, 1972	5
Czechoslovakia	1967, 1973, 1977	Economic Commission for Europe, Standardized input-output tables of ECE countries ..., New York: United Nations, various years	1
Czech Republic	1995	OECD, rev. 2	1
Czech Republic	2000, 2005	OECD, rev. 3	1
Denmark	1966, 1970, 1975, 2005	http://www.dst.dk	1
Denmark	1980, 1985,1990	http://www.dst.dk	1
Denmark	1995, 2000	http://www.dst.dk	1
Dominican Republic	1962	United Nations Economic Commission for Latin America, Tablas de insumo-producto en América Latina, Santiago de Chile: Naciones Unidas, 1983	5
Algeria	1974	UNIDO, Input-output tables for developing countries, New York: United Nations, 1985	4
Ecuador	1972, 1975	United Nations Economic Commission for Latin America, Tablas de insumo-producto en América Latina, Santiago de Chile: Naciones Unidas, 1983	4
Egypt	1966, 1986	Elkhafif, Mahmoud AT. The Egyptian economy: A modeling approach. Greenwood Publishing Group, 1996.	3
Egypt	1973	UNIDO, Input-output tables for developing countries, New York: United Nations, 1985	3
Spain	1962	Economic Commission for Europe, Standardized input-output tables of ECE countries for the years around 1959, New York: United Nations, 1972	5

Spain	1966, 1975	Economic Commission for Europe, Standardized input-output tables of ECE countries ..., New York: United Nations, various years	1
Spain	1995, 2000, 2004	OECD, rev. 3	1
Estonia	1997, 2005	OECD, rev. 3	1
Finland	1965, 1970	Economic Commission for Europe, Standardized input-output tables of ECE countries ..., New York: United Nations, various years	1
Finland	1995, 2000, 2005	Eurostat	1
Fiji	1972	UNIDO, Input-output tables for developing countries, New York: United Nations, 1985	1
France	1959, 1965	Economic Commission for Europe, Standardized input-output tables of ECE countries ..., New York: United Nations, various years	1
France	1972, 1977, 1980, 1985, 1990	OECD, rev. 1	1
France	1995, 2000, 2005	Eurostat	1
United Kingdom	1963	Economic Commission for Europe, Standardized input-output tables of ECE countries for the years around 1959, New York: United Nations, 1972	5
United Kingdom	1969, 1975	Economic Commission for Europe, Standardized input-output tables of ECE countries ..., New York: United Nations, various years	1
United Kingdom	1979, 1984, 1990	OECD, rev. 1	1
United Kingdom	1998	OECD, rev. 2	1
United Kingdom	2003	OECD, rev. 3	1
Germany	1959	Economic Commission for Europe, Standardized input-output tables of ECE countries for the years around 1959, New York: United Nations, 1972	5
Germany	1965, 1970, 1975	Economic Commission for Europe, Standardized input-output tables of ECE countries ..., New York: United Nations, various years	1
Germany	1986, 1990	OECD, rev. 1	1
Germany	1995, 2000, 2005	Eurostat	1
Ghana	1968	UNIDO, Input-output tables for developing countries, New York: United Nations, 1985	3
Greece	1958	Economic Commission for Europe, Standardized input-output tables of ECE countries for the years around 1959, New York: United Nations, 1972	5

Greece	1970	Economic Commission for Europe, Standardized input-output tables of ECE countries for the years around 1975, New York: United Nations, 1982	1
Greece	1995	OECD, rev. 3	1
Greece	2000, 2005	Eurostat	1
Guatemala	1971	United Nations Economic Commission for Latin America, Tablas de insumo-producto en América Latina, Santiago de Chile: Naciones Unidas, 1983	1
Guatemala	1992	Bulmer-Thomas, Victor, and Dougal Martin. Construction of an input-output table of the Guatemalan economy. No. 257. Queen Mary University of London, School of Economics and Finance, 1992.	1
Haiti	1971	United Nations Economic Commission for Latin America, Tablas de insumo-producto en América Latina, Santiago de Chile: Naciones Unidas, 1983	3
Haiti	1975	United Nations Economic Commission for Latin America, Tablas de insumo-producto en América Latina, Santiago de Chile: Naciones Unidas, 1983	1
Hungary	1959	Economic Commission for Europe, Standardized input-output tables of ECE countries for the years around 1959, New York: United Nations, 1972	3
Hungary	1965, 1976	Economic Commission for Europe, Standardized input-output tables of ECE countries ..., New York: United Nations, various years	1
Hungary	1998, 2005	OECD, rev. 3	1
Indonesia	1971	Biro Pusat Statistik, Tabel Input-Output Indonesia, 1971	3
Indonesia	1975	UNIDO, Input-output tables for developing countries, New York: United Nations, 1985	3
Indonesia	1980	Biro Pusat Statistik, Tabel Input-Output Indonesia, 1980	3
Indonesia	1985	Biro Pusat Statistik, Tabel Input-Output Indonesia, various years	1
Indonesia	1995, 2000	Biro Pusat Statistik, Tabel Input-Output Indonesia, various years	1
Indonesia	2005	Biro Pusat Statistik, Tabel Input-Output Indonesia, various years	1
India	1951, 1955	Ramana, Duvvuri V. National accounts and input-output accounts of India. Vol. 10. Asia Pub. House, 1969.	2
India	1973	UNIDO, Input-output tables for developing countries, New York: United Nations, 1985	3
India	1993, 1998	OECD, rev. 3	1
India	2003	OECD, rev. 3	1

Ireland	1964, 1969	Economic Commission for Europe, Standardized input-output tables of ECE countries ..., New York: United Nations, various years	1
Ireland	1998	OECD, rev. 3	1
Ireland	2005	OECD, rev. 3	1
Iran	2001	http://www.amar.org.ir	1
Israel	1968, 1972	David Chen, Input-output tables 1968/69, Jerusalem: Bureau of Stats, 1975, 1979	1
Israel	1995	OECD, rev. 3	1
Israel	2004	OECD, rev. 3	1
Italy	1959	Economic Commission for Europe, Standardized input-output tables of ECE countries for the years around 1959, New York: United Nations, 1972	5
Italy	1965, 1970, 1975	Economic Commission for Europe, Standardized input-output tables of ECE countries ..., New York: United Nations, various years	1
Italy	1985	OECD, rev. 1	1
Italy	1995, 2000, 2004	OECD, rev. 3	1
Japan	1960	Economic Commission for Europe, Standardized input-output tables of ECE countries for the years around 1959, New York: United Nations, 1972	3
Japan	1965	Economic Commission for Europe, Standardized input-output tables of ECE countries for the years around 1965, New York: United Nations, 1977	1
Japan	1970, 1975	Economic Commission for Europe, Standardized input-output tables of ECE countries ..., New York: United Nations, various years	1
Japan	1980, 1985, 1990	OECD, rev. 1	1
Japan	1995, 2000, 2005	OECD, rev. 3	1
Kenya	1967 1976	*Input/Output Table for Kenya, Central Bureau of Statistics, various years*	3
Kenya	1971	*Input/Output Table for Kenya, Central Bureau of Statistics, various years*	1
Korea	1970, 1975, 1980, 1985, 1990, 1995, 2005	Bank of Korea	1
Korea	2000	Bank of Korea	1
Lithuania	2000, 2005	Eurostat	1
Luxembourg	1995, 2000, 2005	OECD, rev. 3	1
Latvia	1996	Eurostat	1
Morocco	1975	UNIDO, Input-output tables for developing countries, New York: United Nations, 1985	3

Morocco	1990	Bussolo and Roland-Holst, A Detailed Input-Output Table for Morocco, 1990, Working Paper No. 90, OECD Development Centre, 1993	1
Madagascar	1973	UNIDO, Input-output tables for developing countries, New York: United Nations, 1985	4
Mexico	1950, 1960	United Nations Economic Commission for Latin America, Tablas de insumo-producto en América Latina, Santiago de Chile: Naciones Unidas, 1983	1
Mexico	1970, 1980	Banco de Mexico	1
Mexico	2003	OECD, rev. 3	1
Macedonia	2005	Eurostat	1
Malta	1971	UNIDO, Input-output tables for developing countries, New York: United Nations, 1985	1
Malaysia	1978, 1983, 1987, 1991	*Jadual input-output Malaysia, Kuala Lumpur: Jabatan Perangkaan, various years*	1
Nigeria	1985, 1990	*Input-Output tables of the Nigerian Economy 1985,1987, 1990: Statistical Information for the Nation. Federal Office of Statistics, Lagos, 1996.*	1
Nicaragua	1974	UNIDO, Input-output tables for developing countries, New York: United Nations, 1985	1
Netherlands	1959	Economic Commission for Europe, Standardized input-output tables of ECE countries for the years around 1959, New York: United Nations, 1972	5
Netherlands	1965, 1970, 1975	Economic Commission for Europe, Standardized input-output tables of ECE countries ..., New York: United Nations, various years	1
Netherlands	1981, 1986	OECD, rev. 1	1
Netherlands	1995, 2000, 2005	Eurostat	1
Norway	1959	Economic Commission for Europe, Standardized input-output tables of ECE countries for the years around 1959, New York: United Nations, 1972	5
Norway	1965, 1970, 1975	Economic Commission for Europe, Standardized input-output tables of ECE countries ..., New York: United Nations, various years	1
Norway	1992, 2005	Eurostat	1
Norway	1995, 2000	OECD, rev. 3	1
New Zealand	1995, 2002	OECD, rev. 3	1
Peru	1955, 1963	United Nations Economic Commission for Latin America, Tablas de insumo-producto en América Latina, Santiago de Chile: Naciones Unidas, 1983	5

Peru	1968	United Nations Economic Commission for Latin America, Tablas de insumo-producto en América Latina, Santiago de Chile: Naciones Unidas, 1983	1
Philippines	1974	UNIDO, Input-output tables for developing countries, New York: United Nations, 1985	3
Papua New Guineau	1972	UNIDO, Input-output tables for developing countries, New York: United Nations, 1985	1
Poland	1962, 1967, 1977	Economic Commission for Europe, Standardized input-output tables of ECE countries ..., New York: United Nations, various years	1
Poland	1995, 2000	OECD, rev. 3	1
Poland	2005	OECD, rev. 3	1
Portugal	1959	Economic Commission for Europe, Standardized input-output tables of ECE countries for the years around 1959, New York: United Nations, 1972	5
Portugal	1964, 1970, 1974	Economic Commission for Europe, Standardized input-output tables of ECE countries ..., New York: United Nations, various years	1
Portugal	1995, 2005	Eurostat	1
Portugal	2000	OECD, rev. 3	5
Romania	2000, 2005	Eurostat	1
Russia	1995, 2000	OECD, rev. 3	1
Rwanda	1970	UNIDO, Input-output tables for developing countries, New York: United Nations, 1985	1
Rwanda	1982	*La structure de l'économie Rwandaise à travers son tableau entrées - sorties en 1982 : résultats et méthodologie. Direction générale de la politique économique, Kigali, 1985*	1
Senegal	1959	UNIDO, Input-output tables for developing countries, New York: United Nations, 1985	1
Senegal	1974	Waterbury, John. The political economy of risk and choice in Senegal. Routledge, 2005.	1
Singapore	1973	UNIDO, Input-output tables for developing countries, New York: United Nations, 1985	1
Slovakia	1995	OECD, rev. 3	1
Slovakia	2000	Eurostat	1
Slovakia	2005	Eurostat	1
Slovenia	1996	Eurostat	1
Slovenia	2000, 2005	Eurostat	1
Sweden	1964, 1969, 1975	Economic Commission for Europe, Standardized input-output tables of ECE countries ..., New York: United Nations, various years	1
Sweden	1995, 2000, 2005	Eurostat	1

Thailand	1975	UNIDO, Input-output tables for developing countries, New York: United Nations, 1985	3
Turkey	1963	Economic Commission for Europe, Standardized input-output tables of ECE countries for the years around 1959, New York: United Nations, 1972	3
Turkey	1968	Economic Commission for Europe, Standardized input-output tables of ECE countries for the years around 1970, New York: United Nations, 1982	1
Turkey	1973	Economic Commission for Europe, Standardized input-output tables of ECE countries for the years around 1975, New York: United Nations, 1982	1
Turkey	1996, 2002	OECD, rev. 3	1
Taiwan	1971	UNIDO, Input-output tables for developing countries, New York: United Nations, 1985	1
Taiwan	1996, 2001	OECD, rev. 3	1
Taiwan	2006	OECD, rev. 3	1
Tanzania	1970	UNIDO, Input-output tables for developing countries, New York: United Nations, 1985	1
Uganda	1989	*Input-Output Tables for Uganda (1989 and 1992), Uganda Ministery of Finance and Economic Planning, 1996*	1
Uruguay	1961	United Nations Economic Commission for Latin America, Tablas de insumo-producto en América Latina, Santiago de Chile: Naciones Unidas, 1983	5
United States	1958, 1963	Economic Commission for Europe, Standardized input-output tables of ECE countries ..., New York: United Nations, various years	3
United States	1972, 1977	OECD, rev. 1	1
United States	1985, 1990	OECD, rev. 1	1
United States	1995, 2000, 2005	OECD, rev. 3	1
Yugoslavia	1962	Economic Commission for Europe, Standardized input-output tables of ECE countries for the years around 1959, New York: United Nations, 1972	5
Yugoslavia	1966	Economic Commission for Europe, Standardized input-output tables of ECE countries for the years around 1965, New York: United Nations, 1977	5
Yugoslavia	1970, 1976	Economic Commission for Europe, Standardized input-output tables of ECE countries ..., New York: United Nations, various years	1

South Africa	1971, 1975, 1981, 1984, 1989	ZAF stat	1
South Africa	2000	OECD, rev. 3	1
South Africa	2005	OECD, rev. 3	5
Zambia	1973	UNIDO, Input-output tables for developing countries, New York: United Nations, 1985	3

Notes