Policy Research Working Paper 9491

Measuring Total Factor Productivity Using the Enterprise Surveys

A Methodological Note

David C. Francis
Nona Karalashvili
Hibret Maemir
Jorge Rodriguez Meza

WORLD BANK GROUP
Development Economics
Global Indicators Group
December 2020

Abstract

Total factor productivity is a key element of economic growth and an important performance metric for policy makers. This note describes the methodology for measuring firm-level total factor productivity using the World Bank's Enterprise Surveys cross-country data. It also presents some estimates recovered from the production function. Two versions of the production function are estimated: one Cobb-Douglas, the other a more flexible translog specification. Both estimations are at the two-digit industry level pooling all the Enterprise Surveys data across economies. Evidence is found against using a Cobb-Douglas specification, which is more parsimonious, and in favor of using the flexible translog specification. The resulting firm-level estimates are all published in the Enterprise Surveys database with a unique firm identifier to link to the rest of the Enterprise Surveys data; because the estimates are reliant on new data, they are updated periodically as new Enterprise Surveys data become available. The results show that: (i) median firms operate close to constant returns to scale; (ii) gross-output and value-added production functions provide similar ranking of sectors in terms of output elasticities, capital intensity, and returns to scale; (iii) there is large, firm-level heterogeneity in output elasticities; and (iv) gross-output-based total factor productivity measures are less dispersed than the value-added ones.

This paper is a product of the Global Indicators Group, Development Economics. It is part of a larger effort by the World Bank to provide open access to its research and make a contribution to development policy discussions around the world. Policy Research Working Papers are also posted on the Web at http://www.worldbank.org/prwp. The authors may be contacted at hmaemir@worldbank.org.

Measuring Total Factor Productivity Using the Enterprise Surveys: A Methodological Note *

David C. Francis Nona Karalashvili Hibret Maemir
Jorge Rodriguez Meza†

Keywords: TFP, Enterprise Surveys.
JEL Classification: 012

*This note uses the dataset "Firm Level TFP Estimates and Factor Ratios_September_10_2020.dta" which is published at www.enterprisesurvyes.org in the Firm-Level Datasets for Researchers section. The estimation procedure of this note uses the full cross-country ES data, which is continuously being updated as new data becomes available. Every month estimates are updated, and older datasets are archived and available upon request.

†The authors are from the Enterprise Analysis Unit of the World Bank. We would like to thank Arvind Jain and Rita Ramalho for very helpful comments. The findings, interpretations, and conclusions expressed in this paper are entirely those of the authors. They do not necessarily represent the views of the World Bank and its affiliated organizations, or those of the Executive Directors of the World Bank or the governments they represent.

1 Introduction

Total factor productivity (TFP)—the ability to generate greater value or output with fewer inputs—is one of the key elements of economic growth. There is now a broad consensus that TFP differences account for the bulk of observed cross-country income differences (Klenow & Rodriguez-Clare 1997, Hall & Jones 1999). As Krugman (1994) succinctly put it "productivity isn't everything, but, in the long run, it is almost everything".

Considerable scholarly analysis has been devoted to measuring productivity. The recent, increased availability of detailed firm-level datasets has further intensified the interest in the subject, including investigations of how productivity varies by characteristics of firms (see, for instance, Syverson (2011)). To the extent that data can be disaggregated, researchers can delve into within-economy differences; if data are comparable across economies and across time, cross-economy differences can be examined. For example, a large and growing body of work explores the link between within-industry productivity dispersion across firms and cross-country differences in aggregate productivity (Banerjee & Duflo 2005, Restuccia & Rogerson 2008, Hsieh & Klenow 2009, Bartelsman et al. 2013).

In the absence of comparable census data, researchers have attempted to estimate productivity using survey-based data, which are often the only available data in less developed economies. The Enterprise Surveys (ES), detailed firm-level data collected by the World Bank's (WB) Enterprise Analysis unit, are well suited for such inquiry. To facilitate the study of productivity by researchers and policymakers, the data published with this paper provide estimates of both TFP and factor ratios. The latter, more straightforward estimates are provided as TFP estimation may be troublesome for multiple reasons, e.g. the endogeneity of input choice (Olley & Pakes 1996, Levinsohn & Petrin 2003, Ackerberg et al. 2015). Unlike TFP estimates, some of these ratios are also available for most non-manufacturing firms.

The rest of this paper is organized as follows. Section 2 briefly summarizes the ES data, including steps taken for comparability and regarding outlier observations. Section 3 discusses the estimation of revenue-based TFP, so-called TFPR. Estimates of output elasticities and their derived characteristics are presented in section 4.

2 Data

The World Bank's Enterprise Analysis unit has been conducting surveys using a methodology that allows cross-economy analysis since 2006. To date, over 168,000 face-to-face interviews with top managers and business owners in 144 economies have taken place under this "Global Methodology". This note uses these data to estimate TFP. Surveys not using the Global Methodology are excluded, as are the surveys conducted earlier than 2006. The data from Zimbabwe 2011 are excluded from analysis due to the complications due to hyperinflation just prior to the data collection. An additional 25 surveys are dropped because at least one of the key variables used in the analysis was not collected in these surveys.[1] This leaves 267 surveys in 134 economies and more than 161,000 interviews with top managers and business owners of firms spanning more than 40 different industries (specified by two-digit ISIC

[1]These are: Bangladesh 2007, Benin 2009, Bhutan 2009, Cambodia 2013, Cabo Verde 2009, Central African Republic 2011, Chad 2009, Congo 2009, Eritrea 2009, Fiji 2009, Gabon 2009, Lesotho 2009, Liberia 2009, Malawi 2009, Micronesia 2009, Niger 2009, Pakistan 2007, Rwanda 2011, Samoa 2009, Sierra Leone 2009, Timor-Leste 2009, Togo 2009, Tonga 2009, Vanuatu 2009, and the República Bolivariana de Venezuela 2006.

Rev. 3.1 code). Of these interviews, more than 90,000 are with top managers and business owners of manufacturing firms, for which we provide TFPR estimates. Factor ratios using labor costs and revenues are provided in the associated dataset for most firms in the sample, including firms in selected services sectors covered by the ES.

To construct TFPR, we need information on sales (Y), employment (L), capital stock (K), and intermediate inputs (M). These variables are proxied using the questions available in the data. More precisely, Y is proxied by total annual sales of the establishment (variable d2); K is proxied by the replacement value of machinery, vehicles, and equipment (variable n7a); L is proxied by the total annual cost of labor (variable n2a); and M is proxied by the total annual cost of inputs (variable n2e). For value-added (VA) specifications (presented below), VA is proxied by the difference between total annual sales of the establishment (variable d2) and annual cost of inputs (variable n2e); K and L are the same as in the gross output specification (also elaborated below). The appendix presents each variable used along with the exact wording of the questions.

International Comparability

All the variables used for the productivity estimation are collected in local currency units (LCUs), which are specific to the survey and year. Consequently, the data span different fiscal years. For the estimation of cross-economy regressions all data must be transformed to a common currency-year. To do this, all variables are first converted into U.S. dollars (USD) using the official exchange rate (period average) from the World Development Indicators (WDI).[2] The data are then deflated to 2009 using the GDP deflator for the United States from the relevant reference fiscal year.[3] Note that information on the closing month of the firms' fiscal year is used to adjust exchange rates and deflators for each firm.[4]

Treatment of Outliers

In order to minimize sensitivity to extreme values, outlier firms are eliminated from the analysis. More specifically, outliers in d2 (capturing Y), n7a (capturing K), n2a (capturing L), n2e (capturing M), and VA (d2 minus n2e), as well as outliers in ratios n7a/VA and n2a/VA were turned into missing before estimating the production function. To find outliers in levels, we first transform variables as $\ln(x+1)$, and group observations by economy and broadly defined sector (more precisely, manufacturing and services). Next, we calculate (unweighted) means and standard deviations of these transformed variables within each group. Observations that are more than three standard deviations away from the mean are then marked as outliers and turned into missing. To find outliers in ratios, we first transform variables as $\ln(x)$, and group observations by industry. The three-standard-deviation rule is then applied (unweighted) and the corresponding observations are turned into missing.

[2] WDI indicator code: PA.NUS.FCRF

[3] WDI indicator code: NY.GDP.DEFL.ZS

[4] The fiscal year and its closing month information are given in variables "$d2\_l1\_year\_perf\_indicators$" and "$d2\_n3\_last\_month\_fy\_perf\_ind$" respectively.

Item Nonresponse

Another challenge in estimating total factor productivity is dealing with item nonresponse: i.e., sampled firms do not answer specific questions of the survey. For example, respondents may answer the employment question but not sales. To reduce item non-response, the Enterprise Surveys team follows a strict quality control process that identifies non-responses and contacts firms to complete the data.

Despite this effort, like many other firm-level datasets, the ES also suffers from item nonresponse in variables needed to calculate TFPR. One way to handle the item nonresponse is through imputation. For example, in the U.S. Census Bureau's 2007 manufacturing data 73% of observations have imputed data for at least one variable used to compute TFPR (White et al. 2018). While item non-response may be consequential for most analysis, we do not attempt to address it in the data. We do not employ any of the available imputation or re-weighting methods that assume that data "missingness" is not ignorable and is related to underlying firm characteristics (Little & Rubin 2019). Additionally, the survey (probability) weights included in the data are agnostic to item non-response and the missingness of productivity estimates: weights are not re-adjusted or scaled to account for this missingness.

We exclude observations missing any one of the main production function variables (i.e., sales, labor, capital, or materials). Additionally, note that in cases of negative value-added, logarithms cannot be defined, and thus these observations are not included. This leaves 50,754 observations in 134 countries .

3 Estimating Firm-Level Total Factor Productivity

We begin with a Cobb-Douglas production function (1) for ease of exposition. Throughout this paper, all lowercase variables denote the natural logarithms of the corresponding uppercase variables, representing raw, level values.

$$va_i = \beta_0 + \beta_k k_i + \beta_l l + \epsilon_i \tag{1}$$

Where firm-level value-added (va_i) is a function of inputs of capital (k_i), and labor (l_i). Firms' (logged) TFP is estimated as a sum of the constant and the residual, i.e., $tfp_i = \hat{\beta}_0 + \hat{\epsilon}_i$. We refer to the above model as value-added specification (VAKL). In addition to VAKL, TFP is also estimated using gross-output specification (YKLM) where va_i in (1) is replaced with y_i, output in terms of total revenues, and the right-hand-side has an additional input variable, expenditure on material inputs (m_i).[5] The coefficients β_k and β_l estimate the elasticities of capital and labor, respectively. Throughout, we will denote estimated elasticities by $\hat{\theta}_{input}(i.e., \hat{\theta}_l)$, where $input \in k, l, m$.

While analytically straightforward, this estimation of TFP bears several caveats. First, ordinary least squares estimates of equation (1) may suffer from a simultaneity problem: firms' input choices may be guided by their productivity (Marschak & Andrews 1944). Several methods have been developed in order to address this endogeneity problem (Olley & Pakes 1996, Levinsohn & Petrin 2003, Ackerberg et al. 2015). In these methods, past input decisions (for instance the choice to invest in capital) are

[5] Note that other versions of (1) are also possible, e.g. YKL, or YKELM with E for Electricity. We do not analyze these here as adding a fourth input into a translog production function substantially increases the number of parameters to be estimated.

used to proxy for the current production and use of inputs. To extend future analysis to include these estimations, the ES has started collecting information on these lagged variables of inputs. This will be used in the future as the data become available. Other, firm-level fixed effects methods have been used to estimate average firm-level productivity over time. The ES has constructed longitudinal/panel data for a large number of countries: TFP estimates based on the panel data will also be provided in the future.

Second, there are issues associated with the fact that often only monetary (as opposed to physical) output and input expenditure are observed in typical firm-level data. Such revenue-based TFP is often referred to as $TFPR(TFPR_i = P_i \times TFPQ_i)$, where R stands for revenue and Q for quantity, and P_i denotes the firm's product price. Market dynamics are inseparable within TFPR estimates, which incorporate clearing prices of inputs and revenue-based outputs and can conflate productivity and market (e.g. negotiating) power. As in the case for most firm-level datasets, the ES collect information on revenues and firm-level line item costs (rather than physical inputs and outputs), and hence TFPR is the only measure that can be estimated using the ES data. For a recent discussion of these and other issues in estimation see for instance Foster et al. (2008), Hsieh & Klenow (2009).

A third caveat relates to the importance of the functional form of the production function. The Cobb-Douglas specification in equation (1) assumes a constant elasticity of output, regardless of other output choices. These elasticities are constant and in the form of β_k and β_l. In other words, a firm's elasticity of capital output, for example, does not depend on its use of labor: labor-intensive firms expect the same elasticity of output of capital as non-labor-intensive ones. This assumption may be unrealistic in two ways. First, imposing one production function on firms in different industries is almost surely too restrictive. And indeed, most of the empirical literature on productivity defines industries as narrowly as data permit (Syverson 2011). The ES estimations address this point with a very practical solution: TFPR is estimated separately for each industry — grouped by two-digit ISIC codes — over pooled economies.[6] Second, the assumption of constant elasticities of output for all three (or two) inputs may be too stringent even within industries defined at the two-digit level: so, we also consider a more flexible functional form, the translog specification, which does not impose this restriction.[7] Table A.3 in the Appendix presents the 16 industries with separate estimations.

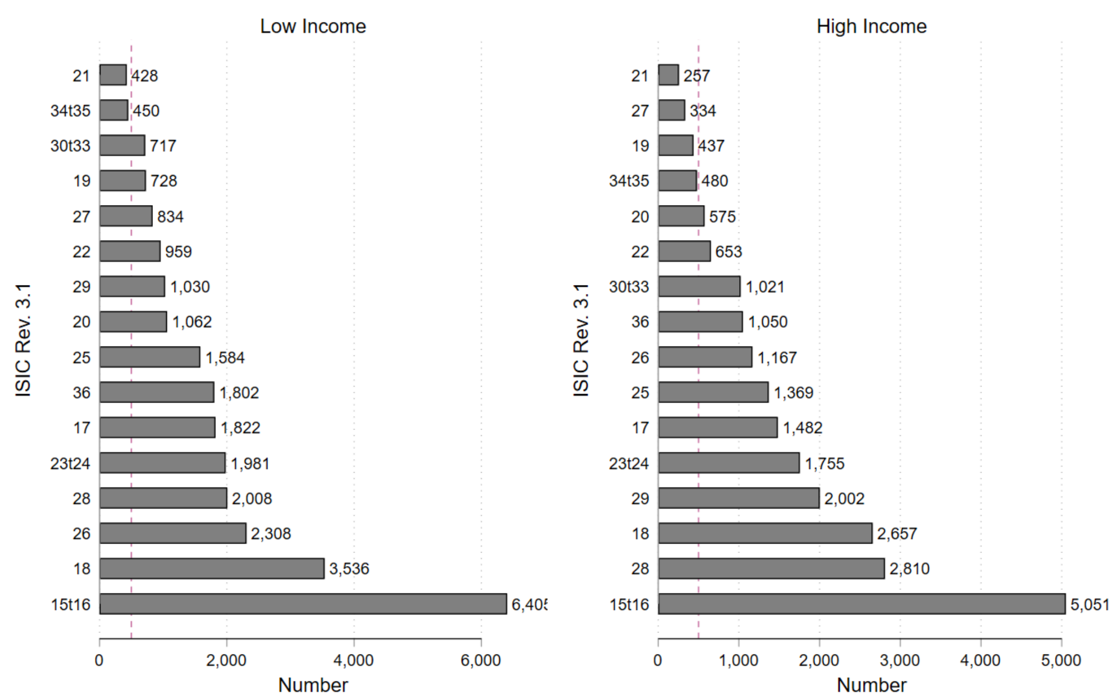
Hence, the estimations assume that the production function, either Cobb-Douglas or translog, is sector-specific but common across countries. To address this rather restrictive assumption, the specification is enriched as follows. First, in order to control for potential differences in production technology between countries, wherever possible, the production coefficients are allowed to vary by the income-level grouping of the corresponding economy by adding interaction terms between income group and factor inputs. The income levels are grouped according to the WB classification (low-income and lower middle income grouped as low-income and upper-middle income and high income grouped as high income) as of the year in which each survey was conducted and are denoted with I_c (equals 1 for high-income). Empirical investigation of the stability of our estimates revealed that this income grouping is appro-

[6] The production functions could in principle be estimated by country and sector. However, estimating production coefficients separately by country-sector is difficult with the ES data since there are few observations for most countries within each sector.

[7] Due to low number of observations in the current dataset, four groups of industries are defined: group 15 and 16: food, beverages and tobacco; group 23 and 24: refined petroleum, nuclear fuel and chemicals; group 30,31,32 and 33: electrical machinery and electronics; and group 34 and 35: transport equipment.

priate if the number of observations per industry and income group is at least 500. For industries with fewer than 500 observations per income group, the coefficients are estimated across all economies (removing I_c). The number of observations by industry and income group is presented in Figure 1.[8] All industries except 19 (leather), 21 (paper), 27 (basic metals), a group of 34 and 35 combined (transport equipment) have more than 500 observations per income group. Hence, productivity coefficients vary across countries with each two-digit sector except for those sectors. The regressions also control for an average economy-level and time effects by including dummy variables for each economy (FE_c) and year FE_t (Halvorsen et al. 1980). An income level fixed effect FE_I is also included in the regression.[9]

Figure 1: Number of Observations by Sector and Income Group as of September 10, 2020



Note: The figure shows the number of observations by two-digit ISIC Rev. 3.1 sector in the low- and high-income economies. The codes represent the two-digit ISIC Rev. 3.1 sectors. Due to low number of observations, some two-digit sectors are combined: group 15 and 16 (15t16): beverages and tobacco; group 23 and 24 (23t24): refined petroleum, nuclear fuel and chemicals; group 30,31,32 and 33 (30t33): electrical machinery and electronics; and group 34 and 35 (34t35): transport equipment.

The functional form of Cobb-Douglas is examined in comparison with the more flexible translog production function. The latter is a second-order Taylor expansion of the Cobb-Douglas function; it interacts each input term with itself and all other combinations of input terms. For the gross output specification this (YKLM) gives:

[8] Note: As the dataset is periodically updated, the number of observations in the production function estimations are subject to change.

[9] A dummy for income group is not subsumed by the country fixed effect because income status can change across survey years. The countries that have changed income group during the survey period are Albania, Colombia, Ecuador, Georgia, Guatemala, Kosovo, Namibia, Paraguay and Peru.

$$
\begin{aligned}
y_{ict} = {} & \beta_k k_{ict} + \beta_l l_{ict} + \beta_m m_{ict} + \underbrace{\beta_{ki} k_{ict} \times I_c + \beta_{li} l_{ict} \times I_c + \beta_{mi} m_{ict} \times I_c}_{\text{coefficients vary by income group}} \\
& + \beta_{kk} k_{ict}^2 + \beta_{ll} l_{ict}^2 + \beta_{mm} m_{ict}^2 + \beta_{kl} k_{ict}.l_{ict} + \beta_{11} k_{ict}.m_{sci} \\
& + \beta_{lm} l_{sci}.m_{ict} + \beta_{klm} k_{ict}.l_{ict}.m_{ict} \\
& + \underbrace{c^{YKLM} + FE_I + FE_c + FE_t + \epsilon_{ict}}_{\text{represents TFP}}
\end{aligned} \tag{2}
$$

The value-added production function (VAKL), which imposes a fixed proportion assumption on material inputs (Leontief), is estimated as follows:

$$
\begin{aligned}
va_{ict} = {} & \beta_k k_{ict} + \beta_l l_{ict} + \underbrace{\beta_{ki} k_{ict} \times I_c + \beta_{li} l_{ict} \times I_c}_{\text{coefficients vary by income group}} \\
& + \beta_{kk} k_{ict}^2 + \beta_{ll} l_{ict}^2 + \beta_{kl} k_{ict}.l_{ict} + \underbrace{c^{VAKL} + FE_I + FE_c + FE_t + \epsilon_{ict}}_{\text{represents TFP}}
\end{aligned} \tag{3}
$$

where subscripts i, c, t index establishments, countries, and year, respectively; c^{VAKL}, and c^{YKLM} are constants which are common across establishments within each industry.

To test whether either the Cobb-Douglas or translog production specification was more appropriate, the joint significance of the translog terms (all interaction and square terms) was tested. Table 1 reports the results of these joint significance tests. Under the gross-output (YKLM) specification, the translog terms are jointly different from zero for all sectors, suggesting that the translog specification fits the data better. Under the value-added (VAKL) specification, the translog terms are jointly significant at the 10% significance level for all except four sectors (17, 21, 29, and 34-35). To ensure comparability across sectors, only translog estimates are reported for all sectors under both specifications in the associated dataset and are used in the rest of the note.

Table 1: Joint Significance Test

	Gross-output (YKLM)		**Value-added (VAKL)**	
Sector (ISIC Rev 3.1)	**F-Stat**	**p-value**	**F-Stat**	**p-value**
ISIC 15, and 16	43.01	0.00	4.22	0.01
ISIC 17	28.96	0.00	1.58	0.19
ISIC 18	29.48	0.00	7.39	0.00
ISIC 19	28.51	0.00	3.53	0.01
ISIC 20	18.22	0.00	7.63	0.00
ISIC 21	54.72	0.00	0.93	0.43
ISIC 22	7.82	0.00	3.57	0.01
ISIC 23, and 24	12.13	0.00	3.21	0.02
ISIC 25	10.98	0.00	8.54	0.00
ISIC 26	46.91	0.00	4.97	0.00
ISIC 27	37.77	0.00	10.45	0.00
ISIC 28	25.81	0.00	2.69	0.04
ISIC 29	7.32	0.00	0.87	0.45
ISIC 30, 31, 32, and 33	18.77	0.00	2.16	0.09
ISIC 34, and 35	20.29	0.00	0.89	0.45
ISIC 36	22.46	0.00	5.18	0.00

Having adopted the translog specification, firm-level TFPR is estimated by:

$$\widehat{TFPR^f_{icf}} = \widehat{\epsilon^f_{ict}} + \widehat{c^f_s} + \widehat{FE^f_I} + \widehat{FE^f_c} + \widehat{FE^f_t} \tag{4}$$

where $f \in VAKL, YKLM$. TFPR is estimated as a sum of the establishment-level residual $\widehat{\epsilon^f_{ict}}$, constant term $(\widehat{c^f_s})$ which are common across establishment within each industry, country-fixed effects $(\widehat{FE^f_c})$, income group fixed effects $(\widehat{FE^f_I})$, year fixed effects $(\widehat{FE^f_t})$ which are common across establishments within industry-country, industry-income group, and industry-year, respectively. The database available on the ES portal contains the firm-level estimates, i.e. $\widehat{TFPR^{YKLM}_{icf}}$ and $\widehat{TFPR^{VAKL}_{icf}}$, alongside the variables used to estimate TFPR. All estimates take into consideration the survey design for the ES by incorporating both stratification and probability (survey) weight information.

4 Estimates

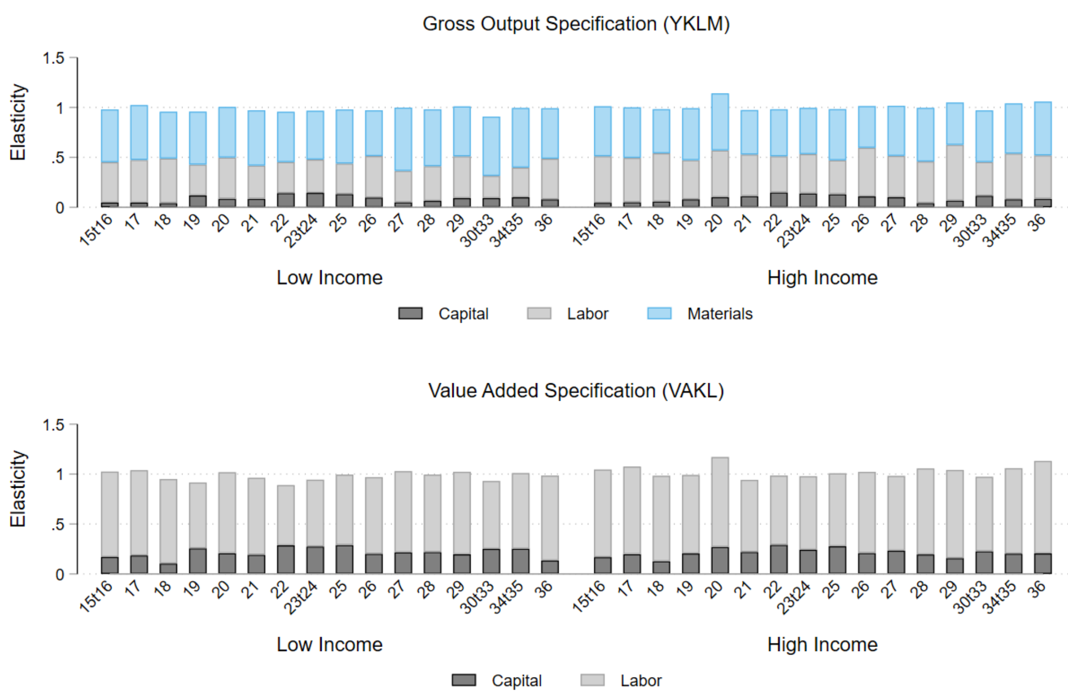
The output elasticity is given by the first derivative of the production function with respect to each input. For instance, under the gross-output production function, the output elasticity of material inputs for high-income economies is estimated as $th\hat{e}ta_m = \hat{\beta}_m + 2\hat{\beta}_{mm}m_{ict} + \hat{\beta}_{km}k_{ict} + \hat{\beta}_{lm}l_{ict} + \hat{\beta}_{klm}k_{ict}l_{ict} + \hat{\beta}_{mi}$. The elasticity for low-income counties is the same except $\hat{\beta}_{mi}$. The elasticities for material inputs depend on the level of use of all inputs used in the production, including labor and capital and not only on the level of use of material inputs.

Translog coefficients $(\hat{\beta}_m, \hat{\beta}_{mm}, \hat{\beta}_{km}, \hat{\beta}_{lm}, \hat{\beta}_{mm}, \hat{\beta}_{klm}, \hat{\beta}_{mi})$ are the same across establishments within an industry and income group. However, unlike the Cobb-Douglas production function, the output elasticities can vary across firms within the same industry/country, because they depend on the level of use of the inputs of production. Hence, small firms can have different elasticities than large firms (just the same, elasticities can vary between small firms, e.g.). This flexible form is an advantage of translog over the Cobb-Douglas production functions, which would have the same output elasticity across establishments within an industry/income group. For example, under the Cobb-Douglas specification, the output elasticity of material input is simply given by $\hat{\beta}_m + \hat{\beta}_{mi}$ for high-income countries and $\hat{\beta}_m$ for low-income countries.

Figure 2 plots estimates of the median output elasticities for each input by sector and income group recovered from the translog production functions. The figure shows that, under the gross-output production function, material inputs has the highest elasticity in all sectors, ranging from 0.41–0.63. The median labor and capital elasticities range from 0.22–0.56 and 0.04–0.15, respectively. The sum of the elasticities, a measure of the returns to scale, ranges from 0.91 to 1.14, indicating that median firms in an industry/income-group operate close to constant returns to scale.

When using the value-added production function, labor input has the highest median elasticity in all sectors. The median labor and capital elasticities range from 0.10 to 0.29, and 0.60–0.92, respectively. The returns to scale range from 0.89 to 1.17. The input factor elasticities and returns to scale obtained from the estimation are in line with earlier findings in the literature De Loecker et al. (2016) for India, and Gandhi et al. (2020) for Colombia and Chile.

Figure 2: Median Output Elasticities by Sector and Income Group

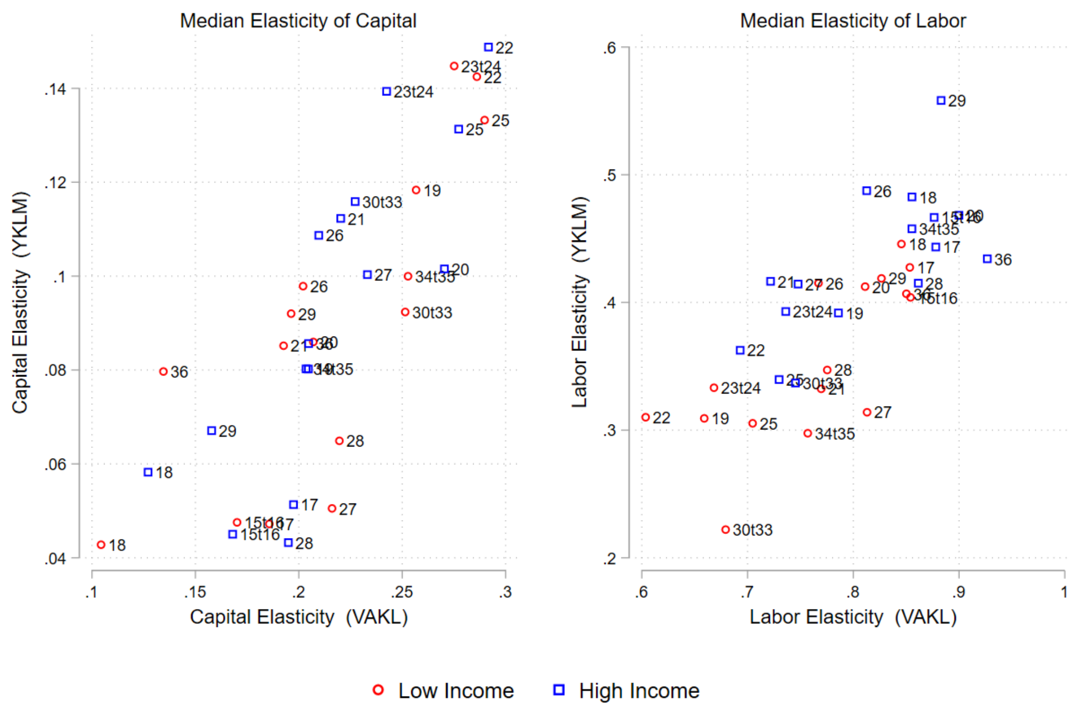


Note: The figure shows the median estimated output elasticity with respect to each factor of production under the gross-output (YKLM) and value-added (VAKL) translog production functions for all manufacturing firms in the low- and high-income economies.

Figure 3 shows the median output elasticities for capital and labor for both the gross output and value-added specifications. The figure clearly shows the ranking of sectors in terms of output elasticities of labor and capital is broadly similar for most sectors. For instance, in low-income countries, the apparel

(18) sector has the lowest output elasticity of capital both under the gross output and value-added specifications.

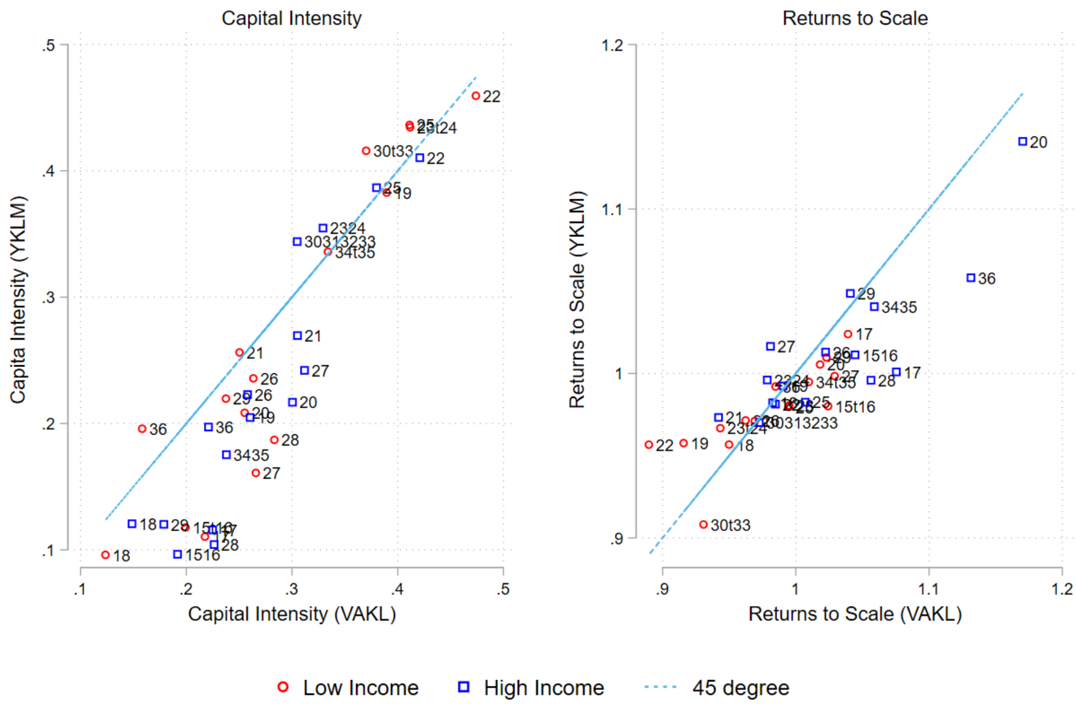
Figure 3: Median Output Elasticities of Labor and Capital



Note: The figure shows the median output elasticities for capital and labor estimated under the gross-output (YKLM) and value-added (VAKL) translog production functions. The dot labels are two-digit ISIC Rev. 3.1 codes.

Figure 4 shows the ratio of the median capital to labor elasticities, which measures the capital intensity in each sector (left panel), and the sum of elasticities which under constant returns to scale add-up to one (right panel). The Apparel (18) and Food (15 and 16) industries in low-income economies are the least capital intensive; Printing and Publishing (22) and Petroleum and Chemicals (23 and 24) in both high and low-income economies are the most capital-intensive industries. The sum of the output elasticities is around one for most of the sectors. Hence, median firms in each sector operate close to constant returns to scale. The gross-output and value-added specifications provide a consistent ranking of sector in terms of the capital intensity and returns to scale.

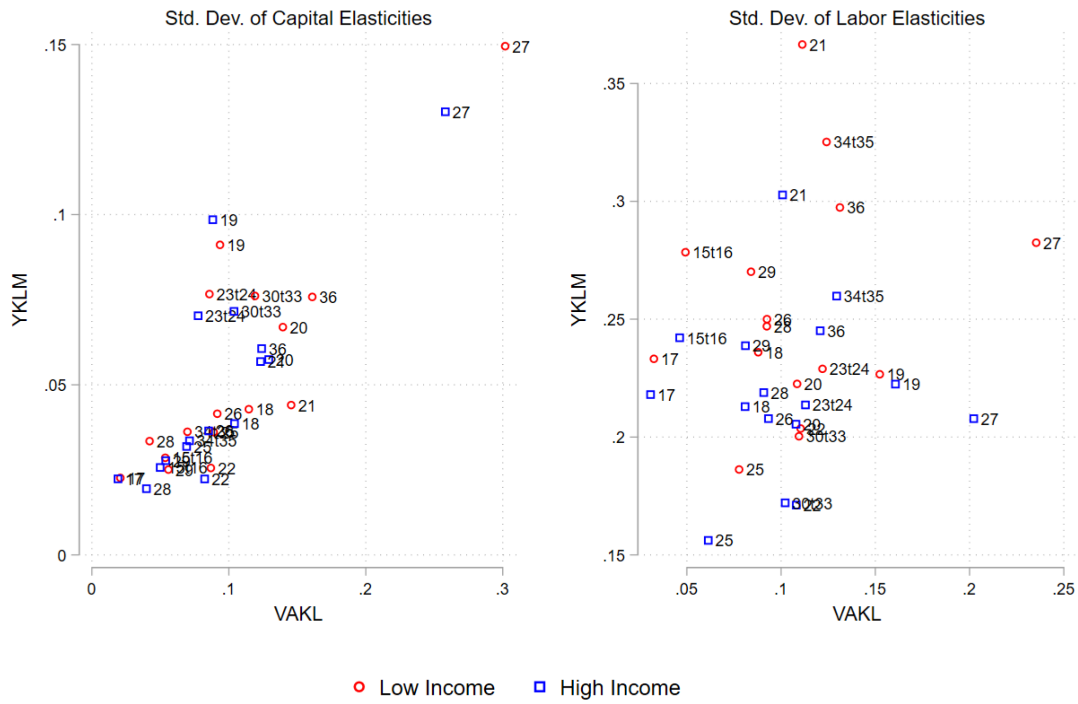
Figure 4: Median Returns to Scale and Capital Intensity



Note: The figure shows the standard deviations for the output elasticities within each industry and income group. The dot labels are two-digit ISIC Rev. 3.1 codes.

Figure 5 shows the standard deviations of output elasticities for labor and capital inputs. The figure shows that there is large, firm-level heterogeneity in the output elasticity of capital and labor in all sectors, although the magnitudes varies across industries. For example, the basic metals sector (27) exhibits the highest firm-level dispersion in output elasticity to capital in both low and high-income economies. This large heterogeneity provides strong evidence against the Cobb-Douglas specification that assumes constant output elasticity.

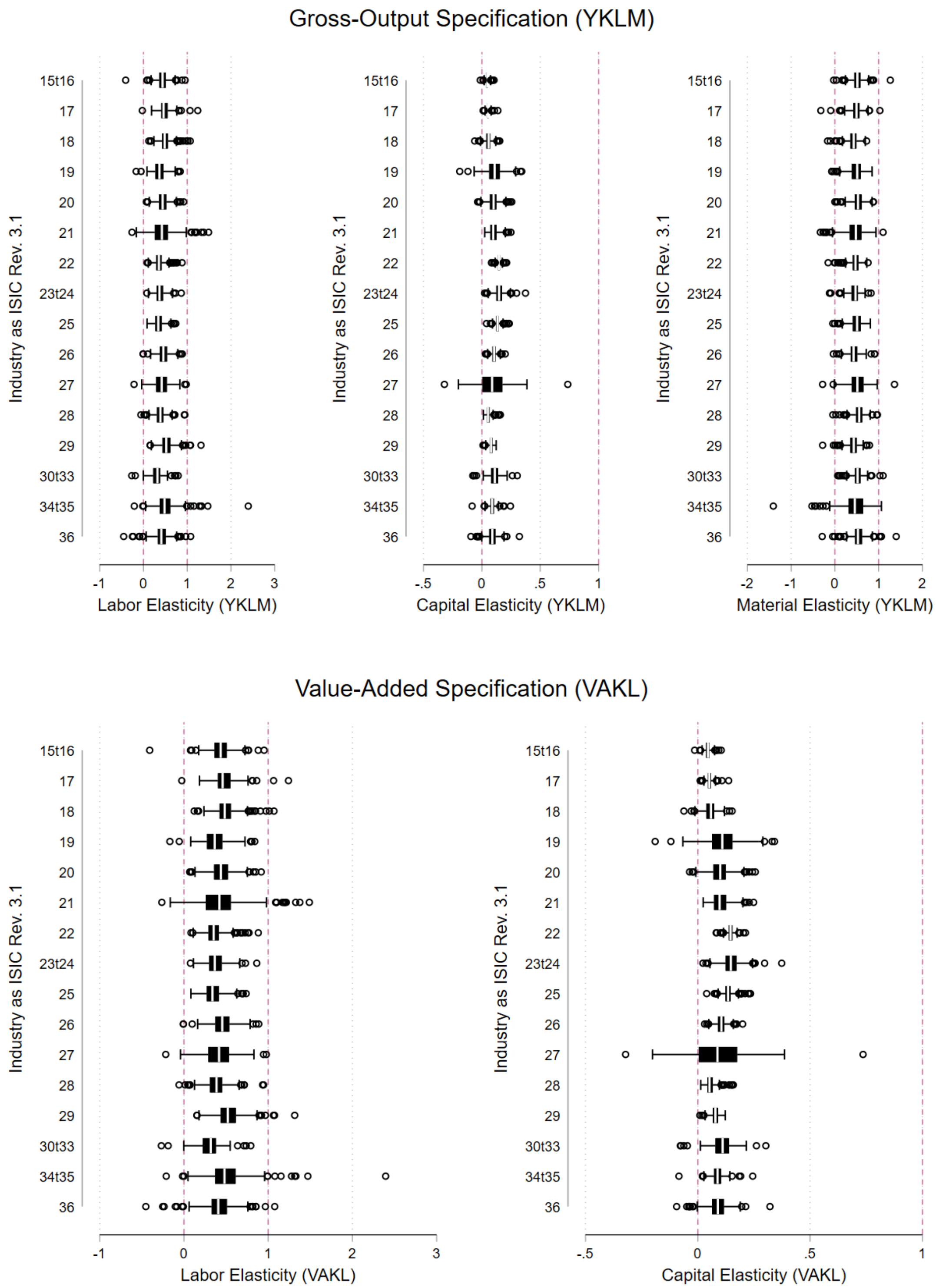
Figure 5: Dispersions of Output Elasticities



Note: The figure shows the standard deviations of output elasticities for capital and labor estimated under the gross-output (YKLM) and value-added (VAKL) translog production functions. The dot labels are two-digit ISIC Rev. 3.1 codes.

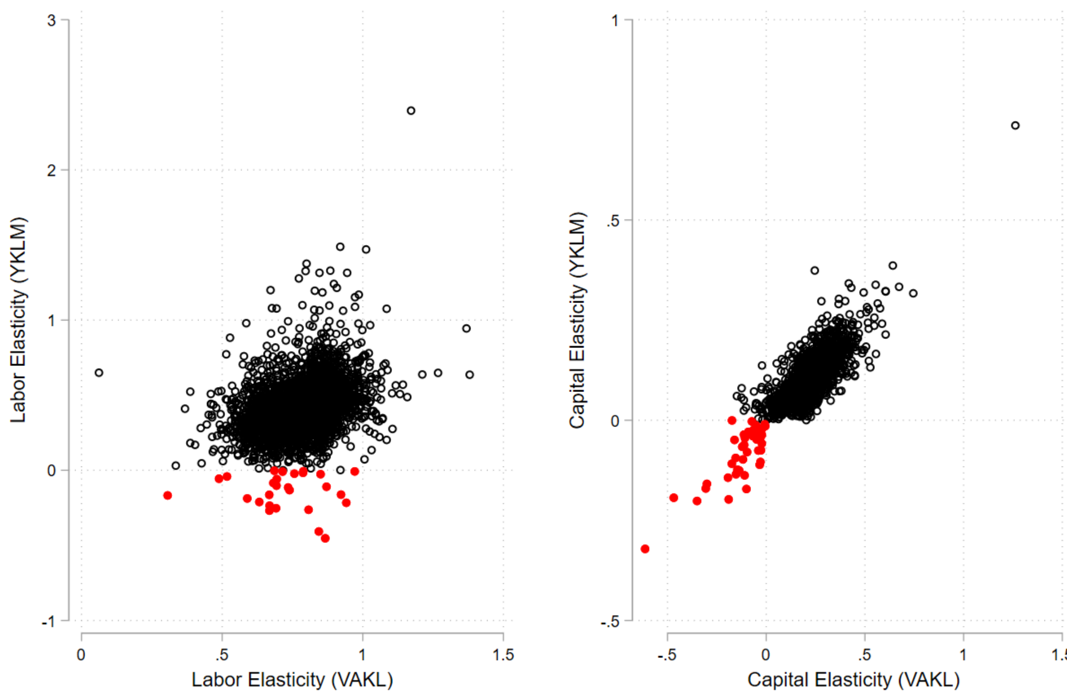
The discussion above suggests heterogeneity in output elasticities within industry and income group. To explore whether the median output elasticities vary across countries within industry, Figure 6 plots the distribution of country median estimates of output elasticities by industry. The median output elasticities are comparable for most countries. However, there are some outliers. The output elasticity estimates turn negative in some countries and sectors. For example, the median elasticities for basic metals (27) can become negative for both capital and labor under the value-added specification.

Figure 6: Output Elasticities by Country



To see the differences in estimates across countries and sectors more clearly, Figure 7 plots the economy-sector level output elasticities of labor and capital. The median estimates of labor elasticities are positive and sensible for most country and sectors except a few under the gross-output specification. The median capital elasticities are positive for most of the country-sector pairs. Tables A.1 and A.2 in the Appendix report the list of country-sector pairs where the median output elasticities of capital are negative (red dots in Figure 7). Using the value-added specification, the median estimates of labor elasticity are positive for all country-sector pairs.

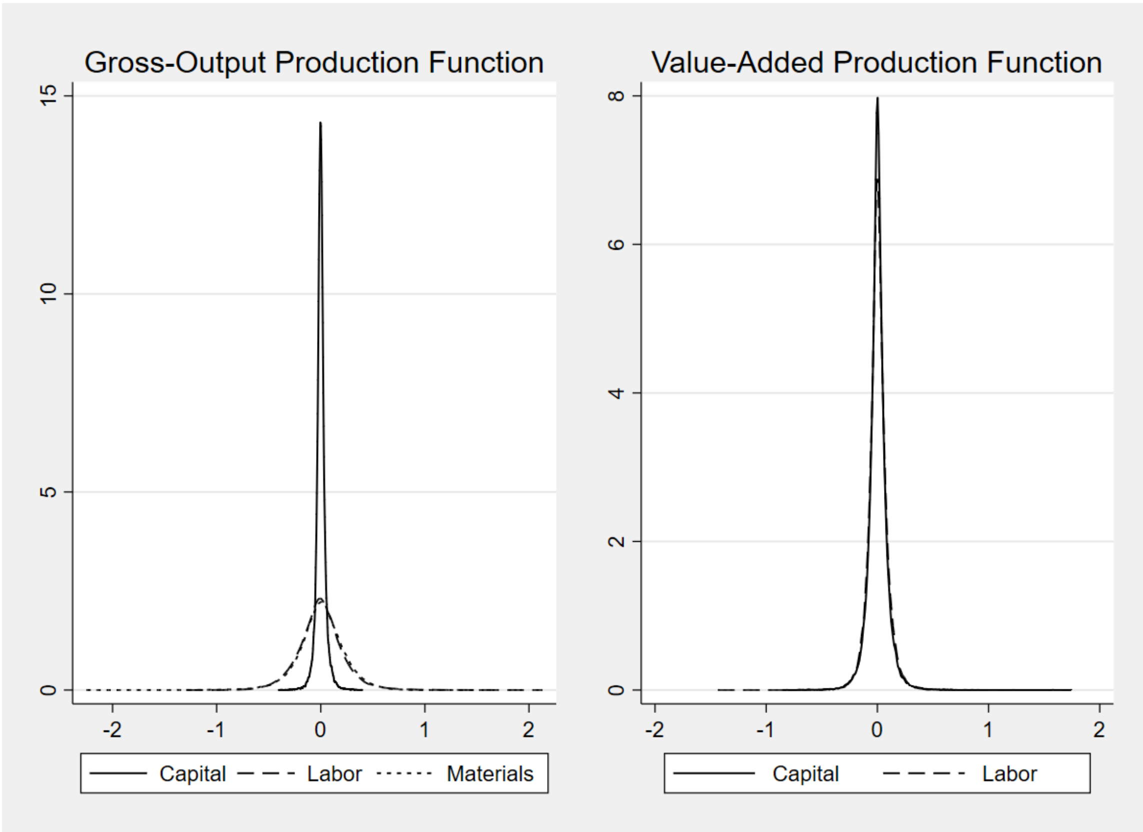
Figure 7: Median Output Elasticities by Country-Sector Pairs



Note: Each point is median output elasticity by country and two-digit ISIC Rev. 3.1 sector. The red dots show country-sector pairs where the median output elasticities of capital are negative.

Figure 8 shows the distribution of output elasticities within countries – adjusted for the country x industry x year fixed effects. The figure shows that there is a substantial heterogeneity in production technology across firms within the same country-sector in a given year.

Figure 8: Distribution of Output Elasticities



Note: The figures show the densities of computed residuals of output elasticities. The residuals are obtained after controlling for country-industry-year fixed effects.

To systematically explore the differences in output elasticities across countries, we regress the output elasticities on the set of fixed effects used in the regressions to quantify their respective explanatory power. Figure 9 plots R-squares for a regression of output elasticities on country, sector, and year fixed effects with no other controls. Under the gross-output specification, a regression of capital, labor and material elasticities: (i) on country fixed effects yields R-squared of 0.04, 0.08, and 0.07, respectively; (ii) on sector fixed effects gives 0.31, 0.06, and 0.03, respectively. Year fixed effects have little explanatory power with R-squared = 0.03 for capital and 0.04 for labor and material output elasticities. The combined effects of country, sector and year fixed effects is 0.35 for capital, 0.14 for labor and 0.10 for material elasticities. Under the value-added specification, the country effects account for 0.08 and 0.05 for capital and labor elasticities, respectively. The sector fixed effects explain 0.17 and 0.33 for capital and labor elasticities respectively.

Figure 9: R-squared for Various Sets of Fixed Effects

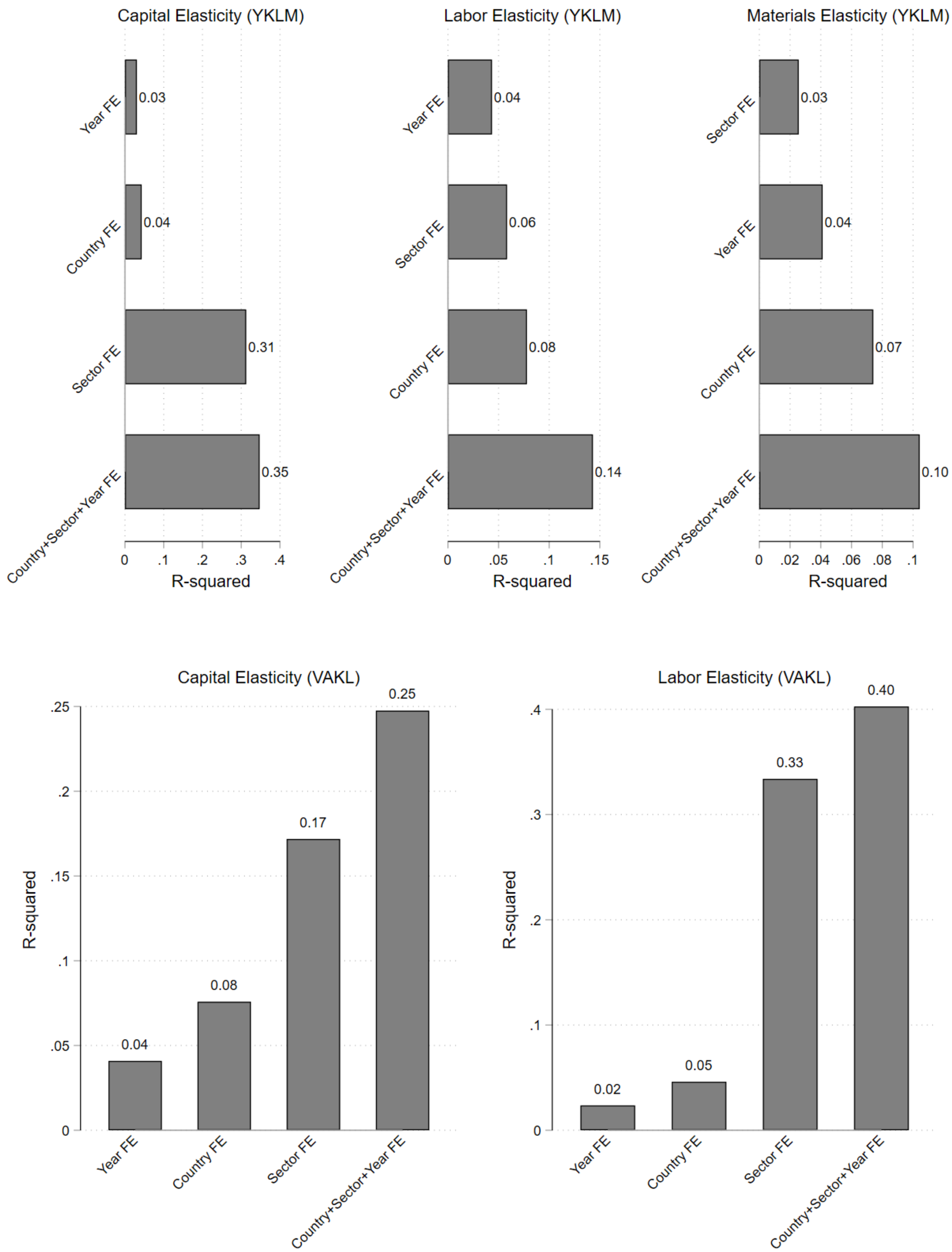
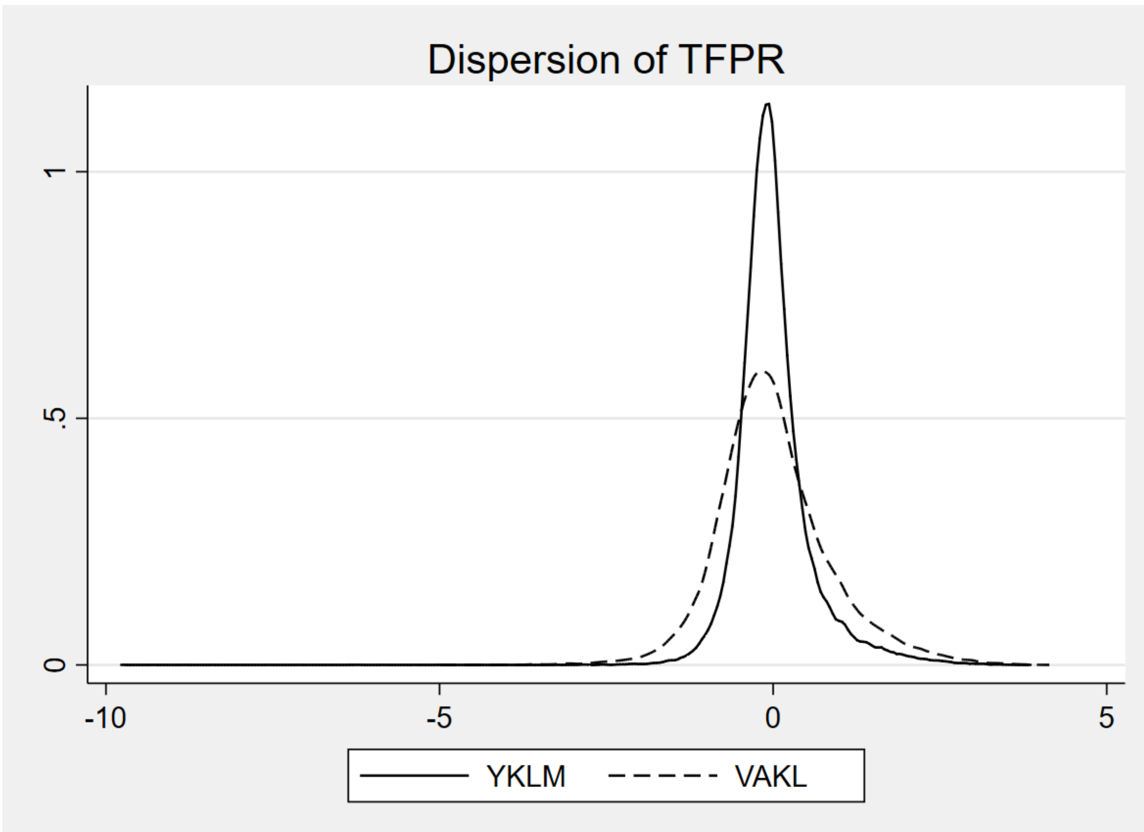


Figure 10 plots the distributions of TFPR (log) measured using gross-output (tfprYKLM) and value-added (tfprVAKL) production functions. The figure shows the distribution of residuals from regressing establishment-level TFPR on country-sector-year fixed effects. Results show that there is a sizable dispersion of TFPR across establishments within industry in a country and that TFPR estimates based on VAKL model are more dispersed than YKLM specification.

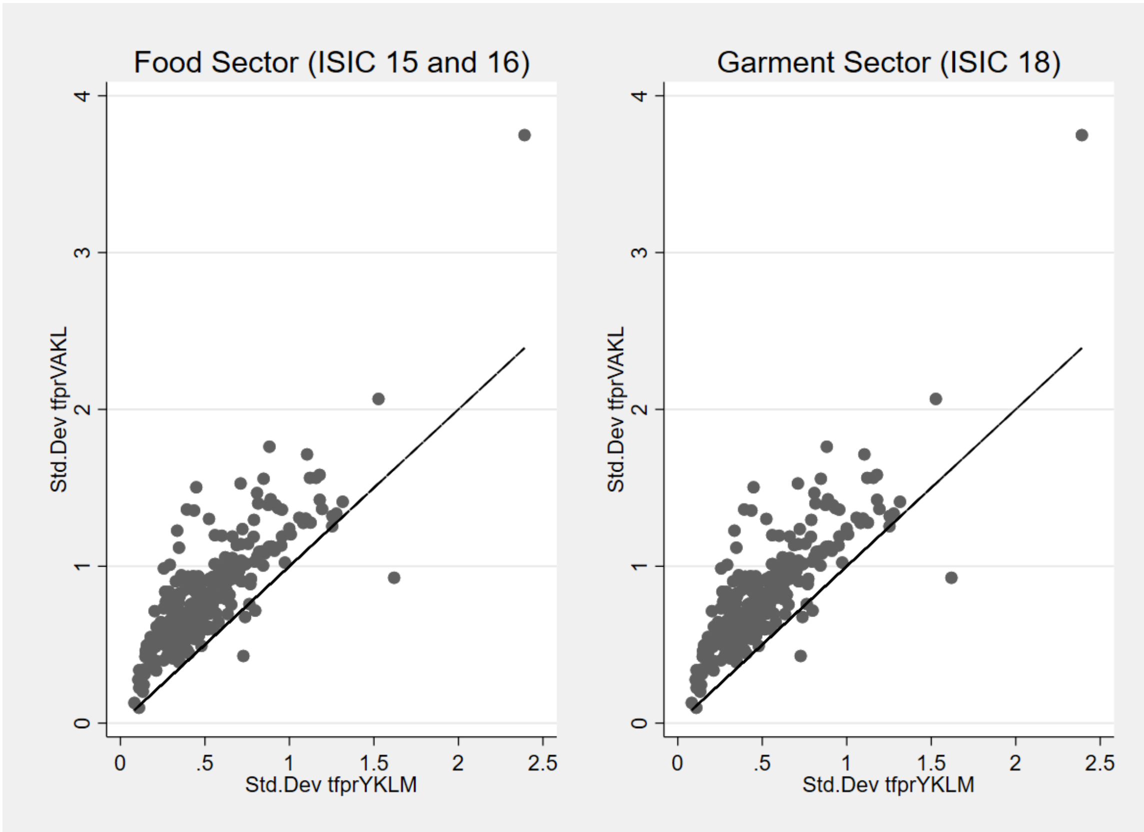
Figure 10: Distribution of TFPR: YKLM vs VAKL Specifications



Note: The figure plots the distribution of log TFPR residuals. The residuals are obtained after controlling for country-industry-year fixed effects. The dispersions are not driven by differences between industries, countries and years.

Figure 11 displays the dispersion of TFPR across establishments measured using gross-output (tfprYKLM) and value-added (tfprVAKL) production functions for the two largest sectors in terms of number of establishments – food and garment. The value-added specifications suggest a much larger TFPR differences across establishments within an industry, as the standard deviations for most of the countries in both sectors lies above the 45-degree line.

Figure 11: Dispersion of TFPR: Gross-output vs Value-Added Specification



5 Discussion

This note presents the background methodology for TFP estimates using the Enterprise Surveys data: it accompanies a firm-level dataset and can, in turn, allow users and researchers to explore firm-level heterogeneity and relationships to other underlying data in the ES. Users can refer to this note for guidance on the use of those estimates. Based on the evidence from this note, TFP estimates from the translog form, using the gross output function are considered as the baseline estimate for standard analysis. However, users can explore other functional forms (including Cobb-Douglas and value-added), keeping in mind the caveats noted here. Users and researchers should note that each of these estimates considers only inputs of capital, labor, and materials in the production function. Alternative estimations taking, for example, elements of the business environment as inputs (not just co-variates of TFP) into the production function would need to be calculated separately. Finally, users should note that as newer surveys are added to the ES portal, these calculations will be repeated, updating TFP estimations.

References

Ackerberg, D. A., Caves, K. & Frazer, G. (2015), 'Identification properties of recent production function estimators', *Econometrica* **83**(6), 2411–2451.

Banerjee, A. V. & Duflo, E. (2005), 'Growth theory through the lens of development economics', *Handbook of economic growth* **1**, 473–552.

Bartelsman, E., Haltiwanger, J. & Scarpetta, S. (2013), 'Cross-country differences in productivity: The role of allocation and selection', *American economic review* **103**(1), 305–34.

De Loecker, J., Goldberg, P. K., Khandelwal, A. K. & Pavcnik, N. (2016), 'Prices, markups, and trade reform', *Econometrica* **84**(2), 445–510.

Foster, L., Haltiwanger, J. & Syverson, C. (2008), 'Reallocation, firm turnover, and efficiency: Selection on productivity or profitability?', *American Economic Review* **98**(1), 394–425.

Gandhi, A., Navarro, S. & Rivers, D. A. (2020), 'On the identification of gross output production functions', *Journal of Political Economy* **128**(8), 2973–3016.

Hall, R. E. & Jones, C. I. (1999), 'Why do some countries produce so much more output per worker than others?', *The quarterly journal of economics* **114**(1), 83–116.

Halvorsen, R., Palmquist, R. et al. (1980), 'The interpretation of dummy variables in semilogarithmic equations', *American economic review* **70**(3), 474–475.

Hsieh, C.-T. & Klenow, P. J. (2009), 'Misallocation and manufacturing tfp in china and india', *The Quarterly journal of economics* **124**(4), 1403–1448.

Klenow, P. J. & Rodriguez-Clare, A. (1997), 'The neoclassical revival in growth economics: Has it gone too far?', *NBER macroeconomics annual* **12**, 73–103.

Krugman, P. (1994), 'The age of diminished expectations: Us economic policy in the 1990s, revised and updated edition'.

Levinsohn, J. & Petrin, A. (2003), 'Estimating production functions using inputs to control for unobservables', *The review of economic studies* **70**(2), 317–341.

Little, R. J. & Rubin, D. B. (2019), *Statistical analysis with missing data*, Vol. 793, John Wiley & Sons.

Marschak, J. & Andrews, W. H. (1944), 'Random simultaneous equations and the theory of production', *Econometrica, Journal of the Econometric Society* pp. 143–205.

Olley, G. S. & Pakes, A. (1996), 'The dynamics of productivity in the telecommunications equipment industry', *Econometrica* **64**(6), 1263–1297.

Restuccia, D. & Rogerson, R. (2008), 'Policy distortions and aggregate productivity with heterogeneous establishments', *Review of Economic dynamics* **11**(4), 707–720.

Syverson, C. (2011), 'What determines productivity?', *Journal of Economic literature* **49**(2), 326–65.

White, T. K., Reiter, J. P. & Petrin, A. (2018), 'Imputation in us manufacturing data and its implications for productivity dispersion', *Review of Economics and Statistics* **100**(3), 502–509.

APPENDIX

A Variables for estimation and associated questions in the questionnaire

- **Sales.** Total annual sales of establishment is measured by variable d2, which records responses to the following question: "In [last complete] fiscal year, what were this establishment's total annual sales for all products and services?"

- **Cost of labor.** Total annual cost of labor is measured by variable n2a, with the corresponding question as follows: "From this establishment's Income Statement for fiscal year please provide total annual cost of labor including wages, salaries, bonuses, social security payments"

- **Materials.** Total annual cost of inputs is measured by variable n2e, with the corresponding question asked only to the manufacturing firms as follows: "From this establishment's Income Statement for fiscal year please provide total annual cost of raw materials and intermediate goods used in production"

- Total annual cost of finished goods is measured by variable n2i, with the corresponding question asked only to the services firms as follows: "From this establishment's Income Statement for fiscal year please provide total annual cost of finished goods and materials purchased to resell"

- **Labor.** Total number of workers is measured by variable l1, with the corresponding question as follows: "At the end of [the last complete] fiscal year, how many permanent, full-time individual worked in this establishment? Please include all employees and managers (Permanent, full-time employees are defined as all paid employees that are contracted for a term of one or more fiscal years and/or have a guaranteed renewal of their employment contract and that work a full shift)

- **Capital.** Price of machinery, vehicles, and equipment is measured by variable n7a, with the corresponding question as follows: "Hypothetically, if this establishment were to purchase [machinery, vehicles, and equipment] it uses now, in their current condition and regardless of whether the establishment owns them or not, how much would they cost, independently of whether they are owned, rented or leased?

Table A.1: List of Country-Industry Pairs with Negative Median Capital Elasticity - YKLM Model

Country	**Year**	**Sector**	**Median Cap. Elast**	**Country**	**Year**	**Sector**	**Median Cap. Elast**
Afghanistan	2008	36	-0.03	Mongolia	2013	18	0.00
Afghanistan	2014	36	-0.09	Mongolia	2013	27	-0.06
Albania	2013	27	-0.19	Mauritania	2006	20	-0.01
Albania	2013	20	-0.04	Mauritania	2006	27	-0.03
Argentina	2017	19	-0.12	Mauritius	2009	27	0.00
Armenia	2009	27	-0.11	Niger	2017	27	-0.13
Armenia	2009	18	-0.01	Nigeria	2007	27	-0.05
Burkina Faso	2009	27	-0.09	Nigeria	2014	30t33	-0.08
Bangladesh	2013	27	0.00	Nicaragua	2010	20	0.00
Bosnia and Herzegovina	2013	19	-0.02	Nicaragua	2016	27	-0.12
Bosnia and Herzegovina	2019	27	-0.14	Nepal	2009	18	-0.01
Bolivia	2017	27	-0.17	Panama	2010	18	-0.02
Côte d'Ivoire	2009	27	-0.11	Peru	2017	27	-0.08
Dominican Republic	2016	27	-0.16	Philippines	2015	27	-0.07
Estonia	2009	19	-0.03	Poland	2009	27	-0.03
Georgia	2013	18	0.00	Paraguay	2006	27	-0.05
Georgia	2013	30t33	-0.05	West Bank and Gaza	2013	36	0.00
Guinea	2006	20	-0.02	Sudan	2014	15t16	-0.01
Guinea	2016	36	-0.02	Sierra Leone	2017	20	-0.02
Guinea-Bissau	2006	18	-0.02	El Salvador	2006	19	0.00
Guinea-Bissau	2006	36	-0.05	South Sudan	2014	27	-0.20
Greece	2018	19	-0.05	Slovak Republic	2019	19	-0.19
Guyana	2010	27	-0.10	Eswatini	2016	18	0.00
Hungary	2009	19	-0.06	Eswatini	2016	36	-0.04
Hungary	2019	19	-0.06	Thailand	2016	27	-0.01
Indonesia	2015	27	-0.04	Tajikistan	2013	36	-0.04
Kazakhstan	2013	18	-0.06	Timor-Leste	2015	36	-0.02
Kazakhstan	2013	27	-0.06	Timor-Leste	2015	30t33	-0.08
Cambodia	2016	27	-0.01	Timor-Leste	2015	18	-0.03
Lao PDR	2016	27	-0.14	Timor-Leste	2015	27	-0.10
Liberia	2017	19	0.00	Trinidad and Tobago	2010	27	0.00
Liberia	2017	27	-0.04	Tunisia	2020	36	-0.04
Lithuania	2019	34t35	-0.08	Turkey	2013	27	-0.32
Morocco	2019	27	-0.17	Uruguay	2017	19	-0.07
Madagascar	2013	27	-0.19	Venezuela, RB	2010	27	-0.20
Mali	2007	27	-0.08	Vietnam	2009	27	-0.03
Mali	2007	30t33	-0.06	Vietnam	2015	27	-0.04
Mali	2016	27	-0.01	Yemen, Rep.	2013	18	-0.01
Myanmar	2014	27	-0.06	Zambia	2007	27	-0.13
Myanmar	2016	27	0.00	Zambia	2013	27	-0.03

Table A.2: List of Country-Industry Pairs with Negative Median Capital Elasticity - VAKL Model

Country	**Year**	**Sector**	**Median Cap. Elast**	**Country**	**Year**	**Sector**	**Median Cap. Elast**
Afghanistan	2014	27	-0.10	Moldova	2013	18	-0.03
Afghanistan	2014	36	-0.15	Madagascar	2013	27	-0.47
Albania	2007	19	-0.04	Mali	2007	27	-0.04
Albania	2013	20	-0.02	Mongolia	2013	27	-0.02
Armenia	2009	27	-0.17	Mauritius	2009	27	-0.07
Burundi	2006	18	-0.02	Namibia	2014	27	-0.04
Burundi	2006	36	-0.06	Niger	2017	27	-0.15
Bosnia and Herzegovina	2019	27	-0.19	Nigeria	2007	27	-0.05
Belarus	2008	20	0.00	Nigeria	2007	36	-0.02
Bolivia	2017	27	-0.10	Nigeria	2014	21	-0.05
Bhutan	2015	21	-0.11	Nicaragua	2010	21	-0.05
Côte d'Ivoire	2009	27	-0.03	Nicaragua	2016	27	-0.15
Cameroon	2016	36	-0.02	Nepal	2009	18	-0.05
Congo, Dem.Rep.	2013	36	-0.02	Panama	2010	36	-0.05
Congo, Dem. Rep.	2013	21	-0.15	Peru	2017	27	-0.10
Congo, Dem. Rep.	2013	18	0.00	Philippines	2009	21	-0.12
Dominican Republic	2016	27	-0.30	Philippines	2015	27	-0.12
Ecuador	2010	21	-0.06	Philippines	2015	21	-0.13
Georgia	2013	30t33	-0.03	Sierra Leone	2017	20	-0.03
Guinea	2006	20	-0.02	South Sudan	2014	27	-0.35
Guinea Bissau	2006	18	-0.01	Eswatini	2016	18	-0.17
Guinea Bissau	2006	36	-0.16	Eswatini	2016	26	-0.02
Guyana	2010	27	-0.12	Eswatini	2016	36	-0.07
Honduras	2016	18	-0.02	Thailand	2016	27	-0.01
Hungary	2013	18	0.00	Tajikistan	2013	36	-0.07
Indonesia	2015	27	-0.11	Timor-Leste	2015	36	-0.06
Kazakhstan	2009	27	-0.40	Timor-Leste	2015	30t33	-0.03
Kazakhstan	2013	18	-0.11	Timor-Leste	2015	18	-0.09
Lao PDR	2016	27	-0.11	Timor-Leste	2015	27	-0.03
Liberia	2017	21	-0.10	Tunisia	2020	21	-0.11
Liberia	2017	27	-0.11	Tunisia	2020	36	-0.03
Lithuania	2009	18	0.00	Turkey	2013	27	-0.61
Lithuania	2013	18	-0.02	Uzbekistan	2008	21	-0.05
Latvia	2019	18	-0.02	Venezuela, RB	2010	27	-0.19
Morocco	2019	21	0.00	Yemen, Rep.	2013	18	-0.01
Morocco	2019	27	-0.31	Zambia	2007	27	-0.14
Moldova	2009	21	-0.04	Zambia	2013	27	-0.03

Table A.3: Industries included in the analysis

ISICs 15 and 16:	Manufacturing of food products and beverages, and manufacturing of tobacco products
ISIC 17	Manufacture of textiles
ISIC 18	Manufacture of wearing apparel; dressing and dyeing of fur
ISIC 19	Tanning and dressing of leather; manufacture of luggage, handbags, saddlery, harness and footwear
ISIC 20	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials
ISIC 21	Manufacture of paper and paper products
ISIC 22	Publishing, printing and reproduction of recorded media
ISICs 23 and 24:	Manufacturing of coke, refined petroleum products and nuclear fuel, and manufacturing of chemicals and chemical products
ISIC 25	Manufacture of rubber and plastics products
ISIC 26	Manufacture of other non-metallic mineral products
ISIC 27	Manufacture of basic metals
ISIC 28	Manufacture of fabricated metal products, except machinery and equipment
ISIC 29	Manufacture of machinery and equipment
ISICs 30, 31, 32, and 33:	Manufacturing of office, accounting and computing machinery; manufacturing of electrical machinery and apparatus n.e.c., manufacturing of radio, television and communication equipment and apparatus, and manufacturing of medical, precision and optical instruments, watches and clocks
ISICs 34 and 35:	Manufacturing of motor vehicles, trailers and semi-trailers, and manufacturing of other transport equipment
ISIC 36	Manufacture of furniture; manufacturing n.e.c.

References

Ackerberg, D. A., Caves, K. & Frazer, G. (2015), 'Identification properties of recent production function estimators', *Econometrica* **83**(6), 2411–2451.

Banerjee, A. V. & Duflo, E. (2005), 'Growth theory through the lens of development economics', *Handbook of economic growth* **1**, 473–552.

Bartelsman, E., Haltiwanger, J. & Scarpetta, S. (2013), 'Cross-country differences in productivity: The role of allocation and selection', *American economic review* **103**(1), 305–34.

De Loecker, J., Goldberg, P. K., Khandelwal, A. K. & Pavcnik, N. (2016), 'Prices, markups, and trade reform', *Econometrica* **84**(2), 445–510.

Foster, L., Haltiwanger, J. & Syverson, C. (2008), 'Reallocation, firm turnover, and efficiency: Selection on productivity or profitability?', *American Economic Review* **98**(1), 394–425.

Gandhi, A., Navarro, S. & Rivers, D. A. (2020), 'On the identification of gross output production functions', *Journal of Political Economy* **128**(8), 2973–3016.

Hall, R. E. & Jones, C. I. (1999), 'Why do some countries produce so much more output per worker than others?', *The quarterly journal of economics* **114**(1), 83–116.

Halvorsen, R., Palmquist, R. et al. (1980), 'The interpretation of dummy variables in semilogarithmic equations', *American economic review* **70**(3), 474–475.

Hsieh, C.-T. & Klenow, P. J. (2009), 'Misallocation and manufacturing tfp in china and india', *The Quarterly journal of economics* **124**(4), 1403–1448.

Klenow, P. J. & Rodriguez-Clare, A. (1997), 'The neoclassical revival in growth economics: Has it gone too far?', *NBER macroeconomics annual* **12**, 73–103.

Krugman, P. (1994), 'The age of diminished expectations: Us economic policy in the 1990s, revised and updated edition'.

Levinsohn, J. & Petrin, A. (2003), 'Estimating production functions using inputs to control for unobservables', *The review of economic studies* **70**(2), 317–341.

Little, R. J. & Rubin, D. B. (2019), *Statistical analysis with missing data*, Vol. 793, John Wiley & Sons.

Marschak, J. & Andrews, W. H. (1944), 'Random simultaneous equations and the theory of production', *Econometrica, Journal of the Econometric Society* pp. 143–205.

Olley, G. S. & Pakes, A. (1996), 'The dynamics of productivity in the telecommunications equipment industry', *Econometrica* **64**(6), 1263–1297.

Restuccia, D. & Rogerson, R. (2008), 'Policy distortions and aggregate productivity with heterogeneous establishments', *Review of Economic dynamics* **11**(4), 707–720.

Syverson, C. (2011), 'What determines productivity?', *Journal of Economic literature* **49**(2), 326–65.

White, T. K., Reiter, J. P. & Petrin, A. (2018), 'Imputation in us manufacturing data and its implications for productivity dispersion', *Review of Economics and Statistics* **100**(3), 502–509.