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THE ROLE OF RESOURCE MISALLOCATION IN CROSS-COUNTRY DIFFERENCES IN MANUFACTURING PRODUCTIVITY

ROBERT INKLAAR
Groningen Growth and Development Centre

ADDISU A. LASHITEW
Rotterdam School of Management

MARCEL P. TIMMER
Groningen Growth and Development Centre

Misallocation of resources across firms leads to lower aggregate productivity. In this paper, we provide new estimates of manufacturing productivity differences across countries and establish by how much they would be reduced if such misallocation were eliminated. Using World Bank survey data for formal manufacturing firms in 52 low- and middle-income countries, we show that manufacturing productivity would increase by an average of 62%, but productivity gaps relative to the United States would remain large. We also find that lower-income countries do not have more to gain from reducing misallocation, as efficiency of resource allocation is uncorrelated with income levels.

Keywords: Productivity, Resource Allocation, Cross-Country Comparisons

1. INTRODUCTION

Total factor productivity (TFP) differences account for much of the income differences across countries [Caselli (2005); Hsieh and Klenow (2010)]. However, measured TFP will reflect not only firm productivity but also any misallocation of resources due to distortions in output and factor markets.[1] Because improving the efficiency of resource allocation across firms is a different challenge than improving firm productivity, it is important to disentangle these two aspects of measured TFP for a sector or economy.

The contribution of this paper is twofold. First, we determine the contribution of resource misallocation to cross-country differences in manufacturing productivity

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for a wide range of low- and middle-income countries. Second, we investigate whether countries with lower income levels would benefit more from improving resource allocation. Earlier contributions to the literature suggest that eliminating resource misallocation would lead to substantial productivity gains, and that the gains would be larger in poorer countries. In a seminal article, Hsieh and Klenow (2009) demonstrated that eliminating misallocation across manufacturing plants in China and India would lead to productivity gains that are larger than in the US, and Bartelsman et al. (2013) found less efficient resource allocation in three Eastern European economies with lower income levels than in Western Europe or the United States. More generally, both studies illuminate how micro-level distortions can have negative macro-level implications.

In the model introduced by Hsieh and Klenow (2009), distortions in firm size and capital/labor ratios lead to variation in the marginal products of capital and labor across firms, within industries. By equalizing marginal products across firms, the productivity gains from eliminating resource misallocation can be quantified. In this paper, we use this methodology to investigate the importance of resource misallocation in the manufacturing sector for a much broader sample of countries than has been done so far. To implement this methodology, we use firm-level data from the World Bank Enterprise Survey (WBES), a standardized survey of firm-level financial and economic data for a wide range of low- and middle-income economies. Our sample covers 52 countries around the year 2005,[2] and the set of countries span much of the development spectrum, from a GDP per capita level of 0.52 percent of the U.S. level (the Democratic Republic of the Congo) to 52 percent of the U.S. level (Slovenia).[3]

We find that most countries would benefit considerably from reducing the degree of resource misallocation to the level seen in the United States, as the average efficiency of resource allocation is 67% of that in the United States. To put these findings into perspective, we estimate relative manufacturing productivity levels, building on and extending the approach of Herrendorf and Valentinyi (2012). Relative TFP across countries is computed as relative value added per worker divided by relative factor inputs (physical and human capital) per worker. To measure relative value added, we estimate relative output prices using not just prices of consumption and investment goods but also prices of exports and imports.[4] Relative factor inputs are computed using economywide data on relative wages and rental prices. We find that even if resource misallocation were eliminated, cross-country TFP differences in manufacturing would remain large: the average observed productivity would rise from 23% to 37% of the U.S. level. Although this represents a substantial reduction of the productivity gap, it is clear that resource misallocation across firms cannot fully account for low aggregate productivity levels.

Our second finding is that we do not find a significant correlation between the efficiency of resource allocation in manufacturing and income levels across our set of countries. This finding suggests that even the richer countries in our sample could still benefit considerably from measures to reduce resource misallocation.

Brazil is an example of this: the World Bank classifies it as an "upper middle-income" country, yet it has a wildly inefficient tax system that distorts capital allocation.[5] In our data, Brazil has an income level in the top quartile of countries, whereas its efficiency of resource allocation is in the bottom half. The formerly Communist countries in Eastern Europe, such as Bulgaria, also tend to have above-average income levels but below-average levels of efficiency of resource allocation, which could reflect their legacy of central planning.

We establish the robustness of these results by considering a range of alternative measurement choices. The main alternative measure of the efficiency of resource allocation is covariance between firm size and labor productivity, favored by Bartelsman et al. (2013). This covariance measure is positively correlated with our measure, based on the Hsieh and Klenow (2009) methodology, and also shows no significant relationship with income levels. Additional alternatives are to consider different types of distortions separately, to vary the elasticity of substitution between product, to vary the treatment of the basic survey data, and to account for the large differences in sample size across countries. Our findings remain robust throughout.

Before we proceed, it is helpful to place our results in a broader context. The methodology we follow in this paper is, in the terminology of Restuccia and Rogerson (2013), an indirect approach to analyzing misallocation, in which the full gap between marginal costs and marginal products of capital and labor is labeled as resource misallocation. This indirect approach contrasts with direct approaches, which analyze the impact of specific frictions—such as financial frictions [Buera et al. (2011); Moll (2014)]—on resource allocation and aggregate productivity. As opposed to such studies, our approach encompasses the effect of many possible frictions but, as a result, cannot be directly tied to specific institutions. Furthermore, by attributing the full gap between marginal costs and marginal products to misallocation, we may be overstating the importance of misallocation: adjustment costs, experimentation by firms with new technologies, and measurement error are all included in our measure of misallocation. The extent of such overstatement, though, will be mitigated by measuring misallocation relative to the United States.

Our analysis relies on the WBES data set, because it allows us to compare a wide range of countries. However, the World Bank's sample frame is restricted to (formal) manufacturing firms with at least five employees, so the survey does not capture informal and smaller formal manufacturing firms. Studying the formal sector is of interest, as firms in this sector operate in an environment that is directly influenced by the labor, capital, and output market institutions and policies that could lead to resource misallocation.[6] Rodrik (2013) finds unconditional productivity convergence in formal manufacturing and argues that this finding is important, as it suggests that a larger formal manufacturing sector will help lower-income countries to catch up. At the same time, this feature of our data means that we cannot reflect on the allocation of resources *between* the formal and informal manufacturing sectors.

Our focus on manufacturing also means that we ignore the type of between-sector misallocation emphasized by Vollrath (2009), Fernald and Neiman (2011), and Gollin et al. (2014). All find that particular sectors, such as agriculture, may employ an inefficiently large part of the labor force. In addition, there may be misallocation within other sectors. For instance, Adamopoulos and Restuccia (2014) show that distortions to farm size can account for part of the cross-country productivity differences in agriculture. Given this broader literature, our finding that misallocation in (formal) manufacturing does not decrease with rising income levels does not automatically carry over to other sectors or the economy as a whole. Because the agricultural sector and informal manufacturing and services tend to shrink with higher levels of development [e.g., ILO (2013)], it could well be that resource misallocation (in a broad sense) and development levels are correlated.

Finally, in the Hsieh–Klenow (2009) model, firm technology is considered exogenous and thus is unrelated to the distortions of factor markets that give rise to resource misallocation. Yet from the broader literature on productivity [e.g., Syverson (2011)], we know that firms engage in technology-enhancing investments, such as spending on research and development (R&D). Furthermore, financial frictions can lead to suboptimal investment in long-run projects such as R&D spending [Aghion et al. (2010)], thus leading to a link between resource misallocation and firm technology. Within this broader context, our study sheds light on the importance of resource misallocation for cross-country productivity differences and our result that misallocation across (formal) manufacturing firms is not correlated with income levels suggests that resource misallocation can be a more subtle force than one might think.

2. THEORETICAL FRAMEWORK

When there are perfect factor and product markets, aggregate productivity reflects only technological differences across countries. But in the presence of distortions that drive a wedge between the marginal product and marginal cost of production factors, aggregate productivity will also reflect resource misallocation [Basu and Fernald (2002); Fernald and Neiman (2011)]. Hsieh and Klenow (2009) argue that misallocation of resources between firms within industries can be important in explaining TFP differences across countries. Applying their model to firm-level data allows us compute a measure of the efficiency of resource allocation, RA, defined as the ratio of observed TFP (A) and (hypothetical) efficient TFP (A^*).[7] The level of TFP in country c relative to the United States can then be decomposed as

$$A_{c\text{US}} = A^*_{c\text{US}} \times \text{RA}_{c\text{US}} \tag{1}$$

We provide a brief sketch of the Hsieh and Klenow (2009) model; see their work for a more extensive exposition. Firm i produces output Y in a monopolistic competition setting with inputs of labor, L, capital, K, and firm-specific productivity,

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A, using a Cobb–Douglas production function:

$$Y_i = A_i K_i^{\alpha} L_i^{1-\alpha} \tag{2}$$

Firms not only are heterogeneous with respect to their productivity, as in Melitz (2003), but also face idiosyncratic distortions of their input and output prices. Two types of distortions are introduced: *output distortions*, which affect the quantity of production while leaving the input mix unaffected, and *capital distortions*, which affect the use of capital relative to labor. These distortions are modeled as taxes on output and capital, leading to the following expression for firm profits π:

$$\pi_i = P_i\,(1 - \tau_{Yi})\,Y_i - wL_i - (1 + \tau_{Ki})\,rK_i \tag{3}$$

where P is the output price of the firm, w is the wage rate, r is the rental price of capital, τ_Y is the output distortion, and τ_K is the capital distortion.

In the model's monopolistic competition setting, profit maximization leads firms to charge a fixed markup over marginal cost, determined by the elasticity of substitution σ. The marginal revenue product of labor (MRPL) and the marginal revenue product of capital (MRPK) are given by the partial derivatives of the revenue function multiplied by the inverse of the markup to correct for rents:

$$\mathrm{MRPL}_i = (1-\alpha)\left[\frac{(\sigma-1)}{\sigma}\right]\left[\frac{P_iY_i}{L_i}\right] = \frac{w}{(1-\tau_{Yi})} \tag{4}$$

$$\mathrm{MRPK}_i = \alpha\left[\frac{(\sigma-1)}{\sigma}\right]\left[\frac{P_iY_i}{K_i}\right] = \frac{r\,(1+\tau_{Ki})}{(1-\tau_{Yi})} \tag{5}$$

Equations (4) and (5) show that the marginal revenue products of labor and capital are affected not only by the wage rate and the rental price of capital but also by distortions. Capital distortions affect the marginal revenue of capital, whereas output distortions affect the marginal revenue products of both labor and capital.

From (4) and (5), we can derive direct expressions for the output and capital distortions:

$$\tau_{Yi} = 1 - \left(\frac{\sigma}{\sigma-1}\right)\left(\frac{wL_i/P_iY_i}{1-\alpha}\right) \tag{6}$$

$$\tau_{Ki} = \left(\frac{\alpha}{1-\alpha}\right)\left(\frac{wL_i}{rK_i}\right) - 1 \tag{7}$$

Firms where the labor share in value added is less than the output elasticity of labor thus face greater output distortions and firms with a lower capital–labor ratio face greater capital distortions. A firm facing large distortions will have high marginal costs and will thus have to charge high prices. This drives a wedge between the firm's physical productivity (referred to as TFPQ) and its revenue productivity (TFPR). Using observed data on revenues and costs, we can compute firm-level TFPR as

$$\text{TFPR}_i = \left(\frac{\sigma}{\sigma - 1}\right)\left(\frac{w}{1-\alpha}\right)^{1-\alpha}\left(\frac{r}{\alpha}\right)^{\alpha}\left(\frac{1+\tau_{Ki}^{\alpha}}{1-\tau_{Yi}}\right) \equiv \left(\frac{\text{MRPL}_i}{1-\alpha}\right)^{1-\alpha}\left(\frac{\text{MRPK}_i}{\alpha}\right)^{\alpha} \quad \textbf{(8)}$$

As (8) shows, TFPR is influenced by both types of distortions. Furthermore, variation in TFPR across firms within an industry reflects only the impact of the distortions, not firm technology. We can determine firm-level TFPQ, which is not affected by distortions, by assuming an elasticity of substitution σ to impute prices and quantities from observed revenues:

$$\text{TFPQ}_i = \left[\frac{(PY)_i}{K_i^{\alpha} L_i^{1-\alpha}}\right]^{\frac{\sigma}{\sigma-1}} \equiv \frac{\text{TFPR}_i}{P_i} \quad \textbf{(9)}$$

Observed industry (and thus also manufacturing) productivity is determined not only by firm TFPQ, but also by the variation in TFPR across firms, and thus by distortions.[8] Conversely, efficient industry (and manufacturing) productivity is determined solely by firm TFPQ levels. The ratio of observed to efficient TFP is thus our measure of the efficiency of resource allocation, which we express relative to the efficiency of resource allocation in the United States as in (1).

We also consider an alternative measure of misallocation, advocated by Bartelsman et al. (2013). This is based on a decomposition of industry labor productivity originally proposed by Olley and Pakes (1996):

$$\frac{Y}{L} \equiv \omega = \sum_i s_i \omega_i = \bar{\omega} + \sum_i (s_i - \bar{s})(\omega_i - \bar{\omega}) \quad \textbf{(10)}$$

Industry labor productivity is a weighted average of firm labor productivity (ω_i), with employment shares as weights, $s_i = L_i / \sum_i L_i$. This can be written as the unweighted average labor productivity (indicated by the upper bar) plus the covariance between firm size (in terms of employment) and firm labor productivity. If this covariance term is positive, it indicates that more productive firms are also larger, and Bartelsman et al. (2013) present a model in which greater distortions to resource allocation lead to lower observed covariances. This measure is a useful alternative because it does not rely on the assumptions of the more extensive theoretical framework of Hsieh and Klenow (2009).

Implementing (6)–(9) requires firm production data and data on wages and the rental rate of capital, which are discussed in the next section. We also need to assume a value for the elasticity of substitution (σ) among products. We follow Hsieh and Klenow (2009) and choose an elasticity parameter of 3, though we also experiment with a higher value of 5.[9] Finally, benchmark values of the output elasticity of capital and labor are required to measure distortions. These benchmark elasticity parameters should come from data that are not distorted and thus reflect the true characteristics of each industry's technology. Following Hsieh and Klenow (2009), we use elasticity parameters from the relatively less distorted

U.S. economy as benchmark values; see the next section for details and Table A.1 for the parameters we use.

3. DATA AND MEASUREMENT

For the estimation of cross-country manufacturing TFP and the efficiency of resource allocation, we use two sets of data. The first set consists of manufacturing output and input levels, based on cross-country price comparisons, to measure aggregate manufacturing productivity levels relative to the United States in 52 countries, and is discussed in Section 3.1. Section 3.2 discusses the WBES, which provides the firm-level financial and economic data that we use to estimate the efficiency of resource allocation within the formal manufacturing sector of each country.

3.1. Data for Manufacturing Total Factor Productivity Levels across Countries

Manufacturing TFP levels are computed as the ratio of manufacturing value added per worker and factor inputs per worker. Manufacturing value added in national currency is available from UN National Accounts data, but to make this comparable across countries, we need relative prices of manufacturing output.[10] Manufacturing value added equals the payments to labor and capital, and to make these factor payments comparable across countries, we need the relative prices of labor and capital and the factor elasticities to combine these into an overall price of factor inputs.

Ideally, relative output price estimates would be based on producer price data, but the lack of dedicated survey data means that alternative approaches have been followed in the literature. When focusing only on manufacturing, some have opted to use exchange rates to compare output from different countries, assuming a relative price of one [e.g., Rodrik (2013)]. An argument in favor of this approach is that many manufactured products are traded and thus more exposed to the pressures of the Law of One Price (LOP). But this argument is not fully convincing, given the systematic deviations from LOP even for products that are internationally traded [Burstein and Gopinath (2014); Feenstra and Romalis (2014)] and the very limited trade in some manufactured products, such as ready-mixed concrete [Syverson (2008)].

The main alternative approach is to use relative prices collected as part of the International Comparison Program (ICP). These prices form the basis of the GDP PPPs disseminated by the World Bank (2008) and are prices of consumption and investment goods and services. Relative output prices for manufacturing are estimated by selecting and combining the prices of goods that are made by manufacturing industries, as in Sørensen and Schjerning (2008), Van Biesebroeck (2009), and Herrendorf and Valentinyi (2012). Given its broad application, it can be seen as the standard approach, yet it has drawbacks as well. Most importantly, the prices of goods consumed or invested domestically do not take into account the prices of exported products, whereas they are influenced by the prices of imported goods. As detailed in the Appendix, we combine ICP price and expenditure data for consumption and investment goods with relative prices of exports and imports from Feenstra and Romalis (2014) and data on industry output, exports, and imports.

To compute manufacturing productivity levels, we need prices of inputs in addition to the price of manufacturing output. We follow the approach of Herrendorf and Valentinyi (2012) and assume that economywide (relative) wages and rental prices apply to manufacturing as well. In effect, this assumes that production factors are mobile across sectors. Our wage measure for the majority of countries is based on the same principle as Herrendorf and Valentinyi (2012), namely the country-average wage level adjusted for differences in schooling.[11] The data source for this measure is the Penn World Table, version 8.0 [PWT; see Feenstra et al. (2015)], and this wage measure is for the year 2005 and covers total labor compensation.[12] For a few countries, we use economywide wages that are not adjusted for differences in schooling, also from PWT and for 2005. For the remainder of countries, we compute the median manufacturing wage from the WBES, based on labor compensation and the number of workers at each manufacturing firm. For those countries, we use overall inflation (of the GDP deflator) between the survey year and 2005 (relative to the United States) to estimate wage levels for 2005.

The relative price of capital input is computed as the relative rental price. The concept is based on Hall and Jorgenson (1967), as adapted by Jorgenson and Nishimizu (1978) for cross-country comparisons. The relative rental price p^K, aggregated over A assets, is computed as

$$\log\left(p_j^K\right) - \overline{\log\left(p^K\right)} = \frac{1}{2}\sum_a \left(c_{aj} + \overline{c_a}\right)\left[\log\left(uc_{aj}\,p_{aj}^I\right) - \overline{\log\left(uc_a\,p_a^I\right)}\right] \quad \mathbf{(11)}$$

where $uc_{aj} = i_j + \delta_a - dp_{aj}$ is the user cost of capital, with i the nominal interest rate, here taken as the lending rate from the IMF's International Financial Statistics,[13] δ the asset-specific geometric depreciation rate, dp_{aj} the price change of asset a in country j, and $c_{aj} = kc_{aj}/\sum_a kc_{aj}$. Here $kc_{aj} = uc_{aj}\,p_{aj}^I K_{aj}$ and K_{aj} is the capital stock of asset a in country j. In this expression, a bar over a variable indicates the arithmetic mean across countries. This means that each country is compared with a (hypothetical) average country to ensure that the resulting relative price measure does not depend on the base country that is chosen [see Caves et al. (1982)].[14]

Capital stocks, asset deflators, and deprecation rates are the same as used for the PWT, and these data are described in detail in Feenstra et al. (2015). Capital stocks are built up from investment by asset using the perpetual inventory method, based on time series going back as far as 1950. These investment series are partly

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taken from the OECD National Accounts database and EU KLEMS, and partly estimated based on ICP expenditure data and the commodity flow method.

The final elements we need for computing relative productivity (as well as for computing distortions; see (6)–(8)) are the elasticity parameters for weighting the prices of labor and capital. We assume that the output elasticities of capital and labor in each manufacturing industry are well approximated by the U.S. cost shares in the same industry. This follows the approach of Hsieh and Klenow (2009), where variations in observed factor shares relative to U.S. output elasticities reflect misallocation of resources.[15] We use industry labor and capital cost shares published by the U.S. Bureau of Labor Statistics (BLS) as part of the Major Sector Multifactor Productivity program. The BLS capital share also covers capital income from land and inventories, so it represents the full contribution of capital to value added.[16]

3.2. Data for Misallocation Measurement

The main data source for measuring misallocation within countries is the World Bank's Enterprises Survey (WBES), an ongoing survey that collects firm-level data worldwide. The major advantage of the WBES survey is that it has a systematic data collection process using standardized survey instruments across a broad range of countries. The data set thus provides comparable data that are unique in their extensive country coverage.

It is important to note that the World Bank sample frame consists of formal manufacturing firms with at least five employees. Because the smallest formal firms and all informal manufacturing firms are not part of the data, our measure of misallocation might underestimate overall resource misallocation in manufacturing. Yet it is hard to make more concrete statements on this topic, because reliable data on even the total number of informal workers and their contribution to GDP are still scarce.[17]

Sampling for the WBES is conducted using stratified sampling procedures to ensure representativeness. The first step is determining the number of industry groups that are to be covered across each major sector. For manufacturing, industry grouping is based on the 2-digit ISIC classification. The size of the economy determines the number of industries to be covered, and the most important industries are selected for sampling. In the second stage, the sample size is chosen to ensure a representative sample for the proportion of firms and the average sales in the industry. Further stratification is based on firm size and geographical location to select the firms that are covered by the survey.[18]

WBES data collection started in 2002 and different countries have been covered in different years. Panel data are available for some countries, but the country coverage of the panel data set is limited. For the analysis in this paper, we therefore construct a cross-sectional data set to cover the maximum number of countries around the year 2005. When a country has participated in multiple surveys, we use the data for the year with the largest number of firm observations.

From the WBES data, we select manufacturing firms with complete data on total production, cost of intermediate inputs, capital stock, and labor inputs. Firm value added is measured as the difference between sales and the cost of intermediate inputs. The cost of intermediate inputs is the sum of energy costs (fuel, electricity, and others), the cost of raw materials, and overhead and other expenses. To account for differences in hours worked and human capital, we use labor cost rather than employment as the measure of labor input. The capital stock is measured as the book value of assets, summed across the two categories "machinery, vehicles and equipment" and "land and buildings." From the set of firms with data on all variables, we remove loss-making firms with negative value added. We also follow Hsieh and Klenow (2009) and remove observations that are in the top and bottom percentiles of the two types of distortions and of TFPQ within each country data set.

In our "cleaned" data set, a number of industries have very few usable observations compared with the original sample, with the largest loss of data being due to missing capital stock data. To make sure that the final sample is not too different from the original (representative) sample, we exclude industries if they have fewer than five observations or if the number of usable observations is less than half the original number of observations. In a second screening, we exclude all countries with fewer than 40 observations or where fewer than 40 percent of the original observations remain. These cutoff points should ensure that countries are excluded for which the sample would be much less representative than the original. For sensitivity analysis, we also consider three alternative treatments of the basic WBES data:

1. Excluding the top and bottom 2.5% of observations, rather than the top 1% of observations. This reduces the sample from 52 to 44 countries.
2. Excluding all loss-making firms, rather than only those where losses are large enough to lead to negative value added. This reduces the sample to 40 countries.
3. Excluding industries when there are fewer than 10 observations, rather than industries with fewer than 5 observations. This reduces the sample to 44 countries.

Our baseline data set covers 52 countries; see Table 1 for the complete list. The countries are mostly low- and middle-income countries, with a median GDP per capita of $ 3,164 in 2005 (in PPP-converted US dollars from PWT 8.0); the country with the highest income is Slovenia ($ 21,967) and the one with the lowest income is the Democratic Republic of the Congo ($ 221).[19] Table 1 also provides the number of firm observations per country. The average sample size is close to 400, but the sample size differs considerably across countries. Whereas large countries such as India, Brazil, and China have well over a thousand observations, smaller ones such as Estonia and Swaziland have only around 40 observations, our cutoff point. Because the misallocation estimates are likely to be more reliable for countries with a larger number of observations, we will also consider the robustness of our results using weighted regressions and correlations, giving countries with fewer observations a lower weight.

Table 1. Results and data description by country

	Country	Acronym	Year	Observations	TFP	Efficiency RA	Efficient TFP
	Average			392	0.23	0.67	0.37
	25th percentile			87	0.12	0.58	0.20
	75th percentile			556	0.34	0.79	0.49
1	Angola	AGO	2006	148	0.22	0.71	0.31
2	Argentina	ARG	2010	514	0.26	0.90	0.29
3	Azerbaijan	AZE	2009	62	0.20	0.79	0.25
4	Bangladesh	BGD	2007	1199	0.09	0.74	0.12
5	Bolivia	BOL	2006	162	0.18	0.62	0.29
6	Botswana	BWA	2006	71	0.16	0.51	0.31
7	Brazil	BRA	2003	1360	0.41	0.62	0.66
8	Bulgaria	BGR	2007	347	0.22	0.35	0.63
9	Burundi	BDI	2006	71	0.04	0.64	0.06
10	Chile	CHL	2010	562	0.48	0.61	0.79
11	China	CHN	2003	1203	0.18	0.70	0.26
12	Colombia	COL	2010	508	0.35	0.85	0.41
13	Congo, DR	COD	2006	123	0.12	0.55	0.22
14	Croatia	HRV	2007	199	0.80	0.58	1.38
15	Ecuador	ECU	2006	182	0.18	0.71	0.25
16	Egypt	EGY	2004	538	0.21	0.51	0.41
17	Estonia	EST	2009	40	0.54	0.62	0.87
18	Ghana	GHA	2007	243	0.07	0.72	0.10
19	Guinea	GIN	2006	78	0.06	0.97	0.06
20	India	IND	2002	1563	0.21	0.62	0.34
21	Indonesia	IDN	2003	329	0.15	0.97	0.15
22	Iraq	IRQ	2011	405	0.27	0.50	0.54
23	Kenya	KEN	2007	364	0.19	0.45	0.42
24	Lao PDR	LAO	2009	99	0.12	0.66	0.18
25	Madagascar	MDG	2009	88	0.08	0.64	0.13
26	Malawi	MWI	2005	118	0.10	0.49	0.20
27	Malaysia	MYS	2002	562	0.38	0.45	0.84
28	Mali	MLI	2007	232	0.15	0.70	0.21
29	Mauritania	MRT	2006	57	0.25	1.01	0.25
30	Mauritius	MUS	2005	86	0.45	0.50	0.90
31	Mexico	MEX	2010	928	0.54	0.60	0.90
32	Moldova	MDA	2009	53	0.13	0.61	0.21
33	Mongolia	MNG	2009	99	0.12	0.78	0.15
34	Morocco	MAR	2004	691	0.34	0.78	0.44
35	Mozambique	MOZ	2007	240	0.13	0.26	0.50
36	Namibia	NAM	2006	56	0.37	0.69	0.54
37	Nepal	NPL	2009	59	0.06	0.64	0.09
38	Nigeria	NGA	2007	849	0.14	0.67	0.21
39	Pakistan	PAK	2002	670	0.08	0.29	0.28

TABLE 1. *Continued*

	Country	Acronym	Year	Observations	TFP	Efficiency RA	Efficient TFP
40	Peru	PER	2010	443	0.34	0.79	0.43
41	Philippines	PHL	2003	526	0.14	0.68	0.21
42	Senegal	SEN	2007	194	0.16	0.79	0.20
43	Serbia	SRB	2009	69	0.33	0.74	0.45
44	Slovenia	SVN	2009	56	0.65	0.88	0.74
45	South Africa	ZAF	2007	591	0.44	0.76	0.58
46	Sri Lanka	LKA	2004	298	0.19	0.49	0.39
47	Swaziland	SWZ	2006	42	0.18	0.71	0.25
48	Tanzania	TZA	2006	207	0.10	0.81	0.12
49	Thailand	THA	2004	1242	0.16	0.79	0.20
50	Uganda	UGA	2006	232	0.17	0.58	0.29
51	Vietnam	VNM	2005	1055	0.09	0.87	0.10
52	Zambia	ZMB	2007	265	0.14	0.83	0.17

Notes: "Acronym" is the three-letter ISO code used in the figures. "Year" indicates the year in which the WBES survey that we use was conducted. "Observations" indicates the number of firm observations used. "TFP" shows the measured TFP level (United States = 1). "Efficiency RA" shows the efficiency of resource allocation (United States = 1) and "Efficient TFP" is measured TFP divided by the efficiency of resource allocation.

4. RESULTS

In this section we provide evidence for our two main results. First, we show that removing distortions would lead to substantial gains in TFP, but that the gaps in TFP levels relative to the United States would remain substantial. Second, we show that the efficiency of resource allocation is unrelated to a country's income level; i.e., it is not necessarily the lower-income countries that have most to gain from removing distortions to firm size and capital accumulation.

Table 2 summarizes the efficiency of resource allocation relative to the United States, defined in (1) as observed TFP divided by efficient TFP. Recall that efficient TFP levels would prevail if output distortions from (6) and capital distortions from (7) were removed. Aside from the baseline measure, the table also provides a range of alternatives. All measures refer to the formal manufacturing sector in (up to) 52 countries and are expressed relative to the United States. The United States is not one of the countries in our sample, but a helpful benchmark case, as Hsieh and Klenow (2009) show that it is an economy with relatively small distortions. We therefore use the results on the difference between observed and efficient levels from their study.[20]

The table shows the unweighted average efficiency of resource allocation across the countries, as well as the 25th and 75th percentile values. The first line shows the baseline measure, computed by removing both output and capital distortions. The average country has an efficiency of resource allocation of 67% with an interquartile range between 58 and 79%, all relative to the United States. Lines

TABLE 2. Efficiency of resource allocation in formal manufacturing (United States = 1)

	Average	[25th–75th]
1 Baseline measure	0.67	[0.58–0.79]
Single distortion measures		
2 Only output distortion	0.72	[0.64–0.84]
3 Only capital distortion	0.83	[0.75–0.92]
Alternative data choices		
4 $\sigma = 5$	0.50	[0.38–0.61]
5 Excluding 5% of outliers	0.79	[0.68–0.90]
6 Excluding all loss-making firms	0.72	[0.63–0.81]
7 Excluding industries with <10 obs.	0.64	[0.51–0.75]

Note: Line 1 shows the efficiency of resource allocation [see (1)] based on removing output and capital distortions. Line 2 considers only the effect of output distortions and line 3 only the effect of capital distortions. In line 4, the elasticity of substitution is increased from 3 to 5. In lines 5–7, the basic data are processed using more restrictive criteria; see main text for details. Besides the cross-country average, the 25th and 75th percentile values are shown. The statistics are based on unweighted data for 52 countries, except for the measures "excluding 5% of outliers" (44 countries), "excluding all loss-making firms" (40), and "excluding industries with <10 obs." (44).

2 and 3 consider the effect of removing only output distortions or only capital distortions. Removing only the output distortion in effect assumes that the observed firm capital/labor ratios are efficient and that there are only potential TFP gains from moving to an efficient firm size distribution. The reverse is assumed when only the capital distortion is removed. The efficiency of resource allocation is higher for both "single distortion" measures, which is to be expected because (by assumption) there is less misallocation. The efficiency of resource allocation of the "only output distortion" measures is, at an average of 0.72, closest to the baseline measure, which implies that a distorted firm-size distribution is the main source of resource misallocation. This relates well to Hsieh and Klenow (2009), who emphasize the importance of the firm size distribution in their analysis of misallocation in China and India.

The baseline measure of the efficiency of resource allocation assumes an elasticity of substitution between the firms in an industry, σ, of 3. In line 4 this elasticity is increased to 5, in line with a similar sensitivity check by Hsieh and Klenow (2009). In lines 5–7, we employ more restrictive criteria in processing the basic data: excluding 5% of observations as outliers, rather than 2% (line 5); excluding all loss-making firms instead of only loss-making firms with negative value added (line 6); and excluding industries with fewer than 10 observations rather than 5 (line 7). Increasing the elasticity of substitution lowers the efficiency of resource allocation to 0.5, which implies the largest TFP gains from removing misallocation of all measures considered. Excluding a greater number of outliers or all loss-making firms leads to higher efficiency of resource allocation than the baseline measure. Especially for the measure based on more extensive outlier removal, this is as expected, because firms in the tails of the distributions of the distortions and of efficient TFP levels are most affected by the removal of distortions. Still, the results from removing industries with less than 10 observations (compared with the baseline cutoff point of 5 observations) show that the efficiency of resource allocation can also decrease, to 0.64 in that case.

Bartelsman et al. (2013) provide an alternative measure of the efficiency of resource allocation, namely the size–productivity covariance defined in (10). Based on our data, we find that the average covariance across the 52 countries is 0.16, with an interquartile range from 0.02 to 0.29. The generally positive size–productivity covariances indicate that more (labor) productive firms are typically larger. Indeed, the average is higher than reported in Bartelsman et al. (2013, Table 1) for the three formerly Communist countries in Eastern Europe (Hungary, Romania, and Slovenia), and the 75th percentile value of 0.29 is comparable to the covariances in Western Europe (France, Germany, Netherlands). Because most of the countries we cover have income levels lower than those in Eastern Europe—let alone those in Western Europe—this suggests that there is no straightforward linear relationship between the efficiency of resource allocation and income levels, a result to which we will return later.[21] We also find that the correlation between our baseline Hsieh–Klenow (2009) measure and the size–productivity covariance of Bartelsman et al. (2013) is positive at 0.42 and significantly different from zero at the 1% level. This is encouraging because the two measures are constructed in very different ways and rely on different model assumptions regarding market structure and production technology.

Given a measure of the efficiency of resource allocation, we now ask by how much TFP would increase relative to the United States if distortions were eliminated. Table 1 presents measured TFP levels in manufacturing for the 52 countries, constructed using prices of manufacturing output and factor inputs. As the table shows, the average country in our sample has a TFP level of 23% of that in the United States, with an interquartile range of 12–34 percent. Overall, the range of manufacturing TFP levels is comparable to the range of total economy TFP levels for these countries [Feenstra et al. (2015)], which is in line with the result of Herrendorf and Valentinyi (2012) for their estimates of manufacturing and economywide TFP levels.

The table also shows the efficiency of resource allocation, for which the summary statistics were already shown and discussed in Table 2. The table shows that most countries have an efficiency of resource allocation that is high compared with their TFP levels (both relative to the United States). There are some countries, such as Mozambique, Bulgaria, and Pakistan, where the efficiency of resource allocation is very low, between about one-fourth and one-third of the U.S. level, indicating that those countries have very large potential gains from reallocating resources to the more productive firms. Similarly, there are countries with high levels of efficiency, such as Guinea or Mauritania, where there is little to gain from resource reallocation, despite very low TFP levels.

For China and India, the two countries that Hsieh and Klenow (2009) focus on, we can directly compare their outcomes with ours; see Table A.2. The WBES surveys for these countries were held in different years than the Census data used by Hsieh and Klenow (2009), but in both our results and theirs, the efficiency of resource allocation is higher in China (0.70 in our results, 0.77 in Hsieh and Klenow, 2009) than in India (0.62 and 0.63). Furthermore, the two countries would be in the same decile of our cross-country distribution regardless of whether we used our numbers or theirs. It is comforting that the survey data we rely on to achieve large cross-country coverage do not lead to very different results than the more comprehensive Census data of Hsieh and Klenow (2009).

Dividing observed TFP by the efficiency of resource allocation gives efficient TFP levels, per (1). On the average, the efficient TFP level is 37% of the U.S. level, which represents a gain over observed TFP levels of approximately 60%. In some countries, the gains are even larger; for instance, Mozambique would see its TFP level rise from 13 to 50% because of its very low efficiency of resource allocation. But all countries (except Mauritania) would gain, as their efficiency of resource allocation is below one.

But despite the large gains, efficient TFP levels remain well below those of the United States in all but a few countries, and this is our first main finding. Although removing distortions would be beneficial for productivity, it would not—by itself—be enough to eliminate productivity differences. Furthermore, the summary statistics in Table 2 indicate that this result is robust to the exact measurement of the efficiency of resource allocation. The only case where the efficiency of resource allocation was notably smaller than for the baseline measure was when an elasticity of substitution of 5 was assumed. Using that measure, the average efficient TFP level would be 52%, which is still well below the U.S. level. In that case, though, there would also be six countries with higher (efficient) TFP levels than in the United States, which could indicate that resource misallocation is given too large a role in at least some countries when a higher elasticity of substitution is assumed.

A closer look at the results also suggests the second result, namely that the potential gains from removing distortions are not clearly related to the level of development, as proxied in Table 1 by observed manufacturing TFP levels. This is illustrated more specifically in Figure 1, which plots the efficiency of resource allocation against GDP per capita levels.[22] The figure shows no systematic relationship between the efficiency of resource allocation and GDP per capita levels: the slope coefficient is 0.023 with a (robust) standard error of 0.041. In other words, the poorest countries do not gain more from improving the efficiency of resource allocation; this is our second main finding.

One might argue that—given the variation in the number of firm observations (see Table 1)—the efficiency of resource allocation is more reliably estimated in countries with a larger number of firm observations. With data on 52 countries, the size of our sample is relatively modest, so drastically restricting the criteria for when a country is included or separately analyzing a group of countries with relatively more observations would make it more likely that we would find no significant correlation. So instead, we use weighted regression to ensure that our

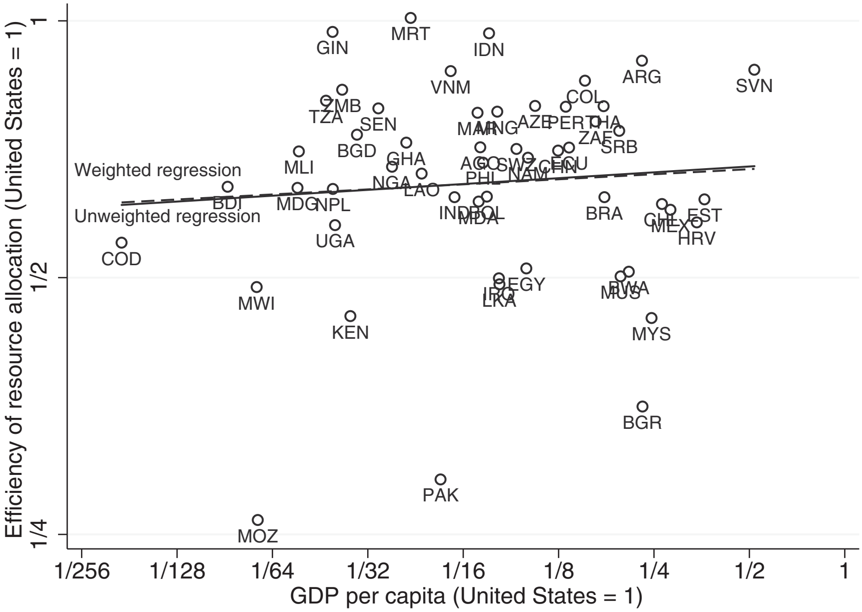

FIGURE 1. The efficiency of resource allocation and GDP per capita. See Table 2 for the country names corresponding to the acronyms. The solid drawn line is the ordinary least squares regression line; the dashed line is the regression line where observations are weighted by the number of firm observations. See also Table 2.

findings are not driven by results for countries with a small number of observations. As the average number of firm observations is 392, this means that the observation for Estonia (with the fewest firm responses, 40) gets downweighted by a factor of ten, whereas the weight on India's observation (with the largest number of firm responses, 1,563) is four times larger than in the unweighted case. The dashed regression line in Figure 1 is based on this weighting and shows how the result is nearly identical to the unweighted result: the slope coefficient is 0.020 with a robust standard error of 0.050.

The figure shows how, for example, Brazil ranks in the top quartile of the GDP per capita distribution, but its efficiency of resource allocation is, at 62%, below the average level of 67% in our 52-country sample. This fits with the broader view of Brazil as a heavily regulated economy where misallocation can thrive. For instance, Brazil ranks 159 out of 189 countries on "Paying Taxes" in the World Bank's (2014) *Doing Business* ranking, because of the high overall tax rate (almost 70% of profits) and 2,600 hours per year needed to comply with the tax code. De Vries (2014) shows how these high tax rates increase capital distortions (and thus resource misallocation) in the Brazilian retail trade sector. Muendler (2004) shows how Brazilian barriers to international trade help low-efficiency firms to remain in business and, again, Brazil scores poorly on the World Bank's *Doing Business* ranking for "Trading across borders" (rank 184 out of 189). This example for Brazil should not be read to imply that a low *Doing Business* ranking leads to a low efficiency of resource allocation, but more as an illustration that a high level of development can coincide with low efficiency of resource allocation. More generally, the research of Muendler (2004) and De Vries (2014) shows that it is not straightforward to infer the effect of specific regulations on resource allocation, given that many other factors can also play a role.

Another example of a country with a relatively high income level, but low efficiency of resource allocation, is Bulgaria. Its efficiency of resource allocation of 35% of the United States (cf. Table 1) is among the lowest in our sample, whereas it is in the top quartile of income levels, with a GDP per capita of 23% of the United States. More generally, there are five transition countries from Eastern Europe in our sample (Bulgaria, Croatia, Estonia, Moldova, and Slovenia), and these tend to have above-average income levels but below-average levels of efficiency of resource allocation. This could reflect their Communist legacy, under which market forces were not the predominant mechanism of allocating resources. In line with this interpretation, Bartelsman et al. (2013) show that the transition countries in their sample had low levels of efficiency of resource allocation (according to their covariance measure) in the early 1990s, but saw rapid improvements in the following years. This is a further indication that misallocation of resources is not primarily influenced or determined by the level of economic development, but rather shaped by country institutions.

The lack of a relationship between the efficiency of resource allocation and the level of development is a robust result. The different measures of the efficiency of resource allocation based on alternative data choices—introduced in Table 2—show (weighted and unweighted) slope coefficients ranging from –0.005 to 0.039, with none close to even the 10 percent significance level. Figure 2 illustrates the relationship between income level and efficiency of resource allocation for the covariance between size and labor productivity favored by Bartelsman et al. (2013); cf. (10). The unweighted regression line has a slope of 0.012 with a robust standard error of 0.025, which is not significantly different from zero. The weighted regression line has a slope of 0.050 (robust standard error of 0.029) and is significantly different from zero at the 10 percent level. The observation for Malawi (MWI), though, is an influential one and the slope coefficient is no longer significant (with a coefficient of 0.044 and a robust standard error of 0.029) if that observation is omitted from the regression.

Figure 3 charts the two single distortion measures against GDP per capita. This figure shows how, for example, Pakistan (PAK) has a low overall efficiency of resource allocation because of severe distortions to the firm size distribution, as reflected in the "only output distortion" measure. Conversely, in Mozambique (MOZ), capital distortions are more important in driving the overall efficiency of resource allocation. Malawi (MWI) has a low efficiency of resource allocation because of output distortions, whereas capital distortions are less of a factor. This can help explain why Malawi was an influential observation in Figure 2,

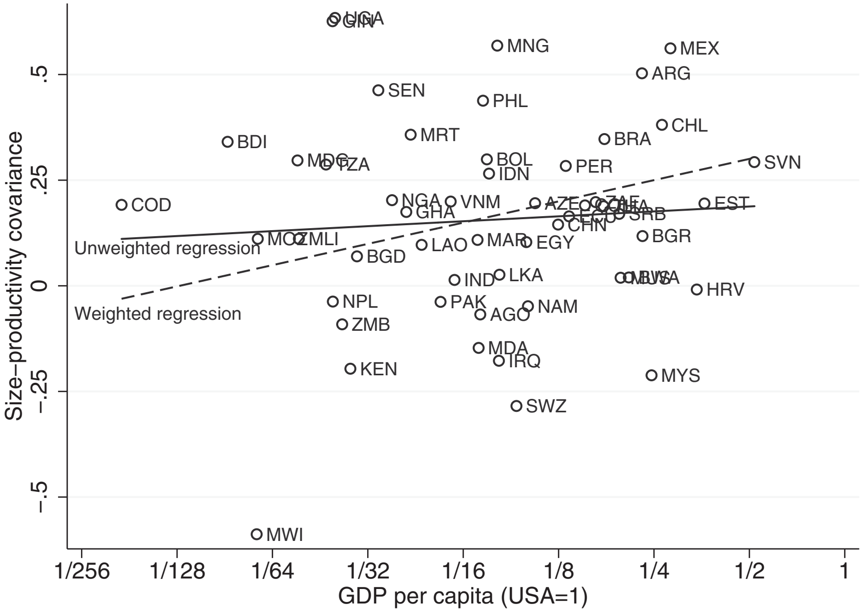

FIGURE 2. The covariance of firm size and labor productivity and GDP per capita. See Table 2 for the country names corresponding to the acronyms. The solid drawn line is the ordinary least squares regression line; the dashed line is the regression line where observations are weighted by the number of firm observations. See also Table 2.

because the size–labor productivity covariance is predominantly influenced by distortions of the firm size distribution.[23] These figures confirm the earlier result of an insignificant relationship between the efficiency of resource allocation and GDP per capita. The slope coefficients for the "only output distortion" measure are even negative at −0.015 (unweighted) and −0.012 (weighted), though far from statistically significant. The slope coefficients for the "only capital distortion" measure are positive at 0.040 (unweighted) and 0.018 (weighted) and again not significantly different from zero. So although we cannot, based on this bivariate analysis, rule out the possibility that there is some connection between the level of economic development and the efficiency of resource allocation, we can conclude that any such connection would need to involve other, potentially more important determinants of the efficiency of resource allocation.

5. CONCLUSIONS

In this paper, we have used survey data covering formal manufacturing firms in a set of 52 low- and middle-income economies in combination with new estimates of relative productivity levels in manufacturing to analyze the role of resource misallocation in accounting for cross-country productivity differences. By applying the Hsieh and Klenow (2009) model of resource misallocation to a broad

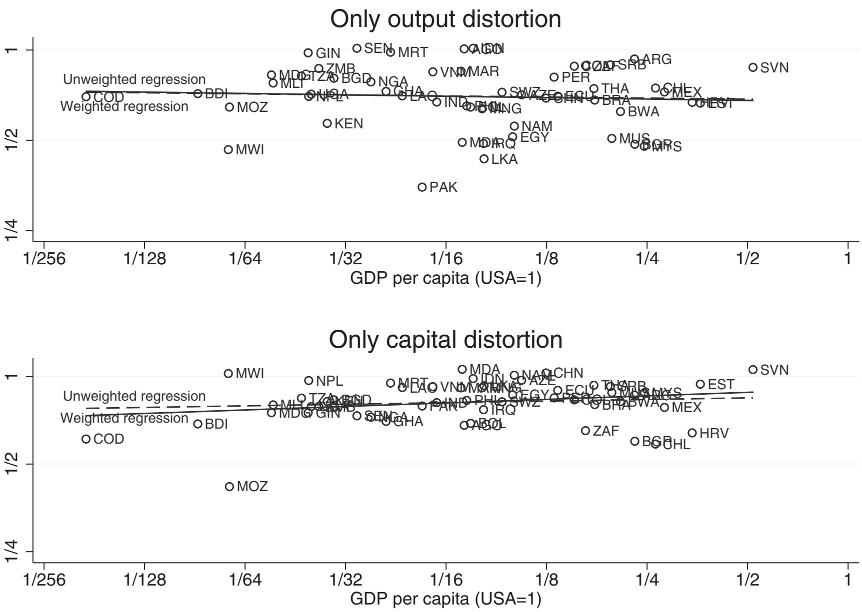

FIGURE 3. Efficiency of resource allocation and GDP per capita – single distortion measures. See Table 2 for the country names corresponding to the acronyms. The solid drawn line is the ordinary least squares regression line; the dashed line is the regression line where observations are weighted by the number of firm observations. See also Table 2.

set of countries, we have provided new evidence on the importance of resource misallocation for aggregate productivity differences and the cross-country pattern of misallocation. The goal of covering a wide range of countries led us to use survey data, rather than industrial censuses, but we have shown that our results are reliable despite the typically smaller sample sizes. We have also shown that the size–productivity covariance measure favored by Bartelsman et al. (2013) to reflect the efficiency of resource allocation shows a broadly comparable cross-country picture, despite large differences in assumptions between the Hsieh and Klenow (2009) and Bartelsman et al. (2013) models. One caveat—which we share with many other studies in this area—is that our data do not cover informal or the very smallest formal manufacturing firms. But although this caveat limits the scope of our findings, our results still point to important potential productivity gains from improving the efficiency of resource allocation.

We find that misallocation of resources between formal manufacturing firms leads to substantially lower manufacturing productivity levels. If resources were allocated efficiently, the marginal product of capital and labor would be equal across firms in an industry, allowing the more productive firms to grow at the expense of their less productive counterparts. In this hypothetically efficient setting, productivity gaps relative to the United States would shrink substantially but remain large: the average manufacturing productivity level across 52 countries

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would increase from 23 to 37% of the U.S. level. Resource misallocation across firms within industries is thus important, yet not the main factor that can explain low manufacturing productivity levels across developing economies. This suggests a role for institutional factors, slow technology adoption, human capital externalities, misallocation of resources across sectors or across formal and informal firms, or any of the other factors that have been associated with productivity differences in the literature.

The second result is that low-income countries do not have most to gain from improving the efficiency of resource allocation. We find that the correlation between the efficiency of resource allocation and GDP per capita is not significant and this result, like the first one, is robust to alternative choices on measuring the efficiency of resource allocation. This result calls for more research on the determinants of resource allocation. The large potential productivity gains from improving the efficiency of resource allocation implies that policies that succeed in unlocking those gains are well worth having, yet such efforts should not be concentrated only in the lowest-income countries.

We find that distortions to the size distribution of firms are of main importance, so identifying barriers to firm growth, such as complex labor regulations or tax codes, would be important. Furthermore, though our findings could not shed light on the allocation of resources between the formal and informal manufacturing sectors, it seems plausible that barriers to firm growth among formal firms could also influence the choice to remain informal. This would be an area where greater availability of basic data would be of great benefit. As it stands, we hope that the estimates of the efficiency of resource allocation presented in this paper will serve as a useful point of reference for future research.

NOTES

1. See, e.g., Basu and Fernald (2002), Hsieh and Klenow (2009), Jones (2011, 2013), and Bartelsman et al. (2013) on this specific topic and Syverson (2011) on how this discussion fits in the broader productivity literature.

2. The WBES surveys were held in the years between 2002 and 2010, so 2005 is a central year.

3. Based on the Penn World Table (PWT), version 8.0, for 2005 [Feenstra et al. (2015)].

4. This follows an approach similar to that of Inklaar and Timmer (2014) and is consistent with the most recent version of the PWT [Feenstra et al. (2015)].

5. Brazil ranks 159th out of 189 countries on “Paying Taxes” in the World Bank’s (2014) *Doing Business* ranking. Muendler (2004) and De Vries (2014) provide analyses of resource misallocation in Brazil.

6. Note that the results of Hsieh and Klenow (2009) also rely on a data set that excludes small and/or informal firms.

7. Note that the efficiency of resource allocation in (1) is the inverse of the TFP gains measure presented by Hsieh and Klenow (2009).

8. See Hsieh and Klenow (2009) for the precise aggregator functions.

9. Based on the median elasticity of substitution estimated by Broda and Weinstein (2006) for their most recent period.

10. Because of missing input–output data, we assume that the price for manufacturing output equals the price for manufacturing value added. The results of Inklaar and Timmer (2014) provide some

support for this assumption, as in their data, the correlation between the output and value-added prices is very high.

11. Herrendorf and Valentinyi (2012) assume that the share of each sector in total labor input equals the share in labor compensation, which is equivalent to assuming the same wage across sectors.

12. Specifically, we multiply exchange rate-converted GDP at current prices by PWT's labor share in GDP and divide by the number of workers times the human capital index relative to the United States.

13. If the lending rate is missing, the yield on treasury bonds or bills (also from the International Financial Statistics) is used.

14. The use of the lending rate means we rely on an external rate of return. The alternative would be to choose the rate of return to exhaust the fraction of GDP not paid out as labor compensation, but such an internal rate of return has a number of practical drawbacks [see Inklaar (2010)].

15. In addition to Hsieh and Klenow (2009), Restuccia and Rogerson (2008) and Fernald and Neiman (2011) also use U.S. cost shares as a (relatively) undistorted measure of output elasticities.

16. Appendix Table A.1 shows the elasticities for individual manufacturing industries. The manufacturing capital share of 40.6% exceeds the 33% of Valentinyi and Herrendorf (2008, Table 1), in part because of the rising U.S. capital share [Elsby et al. (2013)] and in part because our focus is on cost shares of manufacturing firms instead of cost shares from producing manufacturing products.

17. Data from ILO (2013) suggest that the informal sector employs large fractions of the total workforce in many countries, but typically contributes less to GDP, which could imply resource misallocation between formal and informal manufacturing.

18. A full description of the sampling procedure can be found at www.enterprisesurveys.org/methodology.

19. This compares with a median level of GDP per capita of $ 6,573 across all 167 countries in PWT.

20. Specifically, we use the difference of 42.9% between observed and efficient TFP for 1997 from Hsieh and Klenow (2009, Table IV).

21. The results presented in Bartelsmanet al. (2009, Figure 1.9) for 18 countries across a wide range of income levels point to a similar conclusion.

22. Using observed manufacturing TFP levels leads to a very similar figure and subsequent results.

23. The correlation of the firm–labor productivity covariance and the "only output distortions" measure is 0.51 and the correlation with the "only capital distortions" measure is –0.16.

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APPENDIX A

TABLE A.1. Elasticity parameters for measuring misallocation

Industry (ISIC code)	Capital share	Labor share
15	0.489	0.511
17	0.306	0.694
18+19	0.234	0.766
20	0.180	0.820
21	0.422	0.578
22	0.346	0.654
24	0.569	0.431
25	0.381	0.619
26	0.311	0.689
27	0.365	0.635
28	0.290	0.710
29	0.281	0.719
31	0.338	0.662
32	0.305	0.695
34+35	0.234	0.766
36	0.291	0.709
Manufacturing	0.406	0.594

Note: For a few countries in the WBES data set, the 2-digit industrial classifications of industries with ISIC codes 21–22, 25–26, and 27–29 are not known beyond that level of aggregation. In these cases, the average value of the share of labor and capital for the respective 2-digit ISIC industries is used.
Source: Bureau of Labor Statistics (BLS), averaged over the years 2002–2010.

Table A.2. Efficiency of resource allocation in China and India (United States = 1)

	This paper	Hsieh and Klenow (2009)
China	0.70	0.77
India	0.62	0.63

Notes: The efficiency of resource allocation according to this paper is from Table A.1 and refers to data for 2003 in the case of China and 2002 in the case of India. The efficiency of resource allocation implied by the Hsieh and Klenow (2009) results is based on their Table IV, which shows how China's TFP in 2005 would increase by 43.7% relative to the United States and how India's TFP would increase by 84.6% relative to the United States in 1994. The efficiency of resource allocation relative to the United States is computed as (1 + U.S. TFP gain)/(1 + country TFP gain).