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Laura Alfaro
Andrew Charlton
Fabio Kanczuk

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ABSTRACT

We investigate, using firm level data for 79 developed and developing countries, whether differences in the allocation of resources across heterogeneous plants are a significant determinant of cross-country differences in income per worker. For this purpose, we use a standard version of the neoclassical growth model augmented to incorporate monopolistic competition among heterogeneous firms. For our preferred calibration, the model explains 58% of the log variance of income per worker. This figure should be compared to the 42% success rate of the usual model.

Laura Alfaro
Harvard Business School
Morgan Hall 263
Soldiers Field
Boston, MA 02163
and NBER
lalfaro@hbs.edu

Andrew Charlton
London School of Economics
Houghton Street
London, WC2A 2AE, U.K
a.charlton@lse.ac.uk

Fabio Kanczuk
University of São Paulo
R. Dr Alberto Cardoso de Melo Neto 110/131A
Sao Paulo-S.P.-CEP 01455-100
BRAZIL
kanczuk@usp.br

1 Introduction

Cross-country differences in income per worker are widely known to be enormous. Per capita income in the richest countries exceeds than in the poorest countries by more than a factor of fifty. The consensus view in the development accounting literature is that two-thirds of these differences can be attributed to differences in efficiency or total factor productivity (TFP).[1] Researchers have consequently attempted to explain why some countries are able to use their factors of production more efficiently and extract more output than others. The traditional approach to tackling this puzzling question has been to explore the slow diffusion of technology from rich to poor countries.[2]

But there is an emerging and growing body of literature that takes a different approach. Instead of abstracting from the heterogeneity in production units, it focuses on the misallocation of resources across firms (Restuccia and Rogerson 2007, Hsieh and Klenow 2007, and Bartelsman, Haltiwanger and Scarpetta 2006).[3] Policies' and institutions' differential effects on the business climate broadly defined might significantly influence the allocation of resources across firms. The working hypothesis in this literature is that not only the level of factor accumulation matters, but also how these factors are allocated across heterogeneous firms.

Our paper contributes to this literature by performing a development accounting exercise using a new dataset of more than 20 million firms in 79 developing and industrialized countries. Specifically, we develop a simple model of firm dynamics that draws heavily on previous work (Melitz 2003, Hsieh and Klenow 2007) and calibrate it to match our dataset. Our calibration exercise consists in finding the profile of output taxes needed to match each country's firm-size distribution. In practice, this amounts to making each artificial economy's firm-size distribution match the observed firm-size distribution for each country. Taking the United States as a supposedly undistorted benchmark economy, we find the

[1] See Caselli (2005), Hall and Jones (1999), Klenow and Rodriguez-Clare (1997), and Prescott (1998).
[2] Howitt (2000), Keller (2004), and Parente and Prescott (1994).
[3] In particular, Restuccia and Rogerson (2007) using data for the United States, and Hsieh and Klenow (2007) using data for China and India, have found that resource misallocation can lower TFP.

distribution of firm-specific productivities needed to generate its firm-size histogram. We then find, for each country, the firm-size specific distortions needed to match its firm-size histogram, assuming it faces the same distribution of productivity as the U.S. economy. This enables us to calculate how much aggregate output is being wasted due to misallocation attributable to distortions.

To make them directly comparable, our results are reported using the same framework as Caselli (2005). We measure the success of our model by computing cross-country income dispersion under the assumption that all countries have the same productivity. In other words, we calculate the extent to which differences in the misallocation of resources (as well as differences in the amount of physical and human capital resources) explain dispersion in income per worker.

Using a calibrated version of the model, we find misallocation of resources across firms to be a powerful explanatory factor of cross-country differences in income. For our benchmark calibration, the model explains 58% of the log variance of cross-country income dispersion. This figure should be compared to the 42% success rate of the usual model, which considers physical and human capital (average years of schooling).

We redo the basic experiment in sub-samples of the data that are more reliable, choose different parameter calibrations, and truncate the data at different thresholds. We find that the results are not particularly driven by the parameter calibration and or sample differences/biases. We conclude with a discussion of the limitations of, and possible extensions to, our exercise. The acknowledged shortcomings notwithstanding, our results suggest that misallocation of resources is a crucial determinant of income dispersion.

As noted above, the papers closest to the present study are those of Hsieh and Klenow (2007) and Restuccia and Rogerson (2007). The latter, in considering idiosyncratic polices that do not change aggregate capital accumulation and aggregate relative prices, nonetheless find substantial effects of these policies on aggregate output and measured TFP. In their benchmark model, they find that the reallocation of resources implied by such policies can lead to reductions of as much as 30% in output and TFP, even though the underlying range of available technology is the same. Hsieh and Klenow (2007) use plant level information from the Chinese and Indian manufacturing census data to measure dispersion in the marginal products of capital and labor within 4-digit manufacturing sectors. When capital and labor are hypothetically reallocated to equalize marginal products to the extent observed in the United States, the authors find TFP gains of 25%-40% in China and 50%-60% in India. An analogous exercise performed on those two countries using our data yields similar results.

The rest of the paper is organized as follows. Section 2 describes the dataset and its characteristics. The model is presented in section 3, and its calibration detailed in section 4. The results are discussed in section 5. In section 6, we carry out a number of robustness tests, and in section 7, discuss some implicit hypotheses and unaddressed extensions of our analysis. Section 8 presents a tentative conclusion.

2 Data Description

Theoretical work in macroeconomics, trade, and development have recently emphasized the importance of firm heterogeneity and firm level dynamism to economic activity. Cross-country empirical investigations at the firm level, however, are notoriously challenging because of the lack of data and the difficulty of comparing the few datasets that are available.[4] There are few high quality time-series firm-level datasets (mostly in rich countries), but there is a clear need to combine data from multiple countries (in particular, developing countries) in order to understand, for example, the role of institutional policy differences. The problem of a paucity of data is particularly acute for developing countries, and selection problems tend to be associated with biases in and potential endogeneity of the cross-country sample frame. The reason for the data constraint is simple: economic censuses of firms are infrequently collected due to high cost and institutional restrictions that impose an "upper-bound" on research, especially in poor

[4] Bartelesman, Haltinwanger, and Scarpetta (2005) review the measurement and analytical challenges of handling firm level data and attempt to harmonize indicators of firm dynamics for a number of countries. Their harmonized data, however, is available for few countries (mostly industrialized) and for many countries that data is confidential.

countries. No institution has the capacity or resources to overcome the limitation of "lack of census data" for a wide range of countries/periods. Hence, most methodologies face this restriction. The implications of firm heterogeneity, however, merit going forward with the existing data limitations. Researchers have thus sought to find other sources of business "compilations" (registries, tax sources) such as the UNIDO, Amadeus, and WorldBase data set used in this paper.

Dun and Bradstreet's WorldBase is a database of public and private companies in 205 countries and territories.[5] WorldBase reports firm age, number of employees, and the four-digit SIC-1987 code of the primary industry in which a firm operates as well as sales and exports, albeit with much less extensive coverage of the latter two.[6] The data, compiled from a number of sources including partner firms in dozens of countries, telephone directory records, websites, and self-registration, are meant to provide clients with contact details and basic operating information about potential customers, competitors, and suppliers. Information from local insolvency authorities and merger and acquisition records are used to track changes in ownership and operations. All information is verified centrally via a variety of manual and automated checks.

The main advantage of our database is its size. Our original sample included nearly 24 million private firms in 2003/2004. Excluding territories and countries with fewer than 10 observations and those for which the Penn Table 6.1 provides no data left us with observations in 79 countries that exhibited

[5] Dun & Bradstreet is the leading U.S. source of commercial credit and marketing information since 1845. D&B operates in 205 countries and territories either directly or through affiliates, agents, and associated business partners. Early uses of the D&B data include Caves' (1975) size and diversification pattern comparisons between Canadian and U.S. domestic firms as well as subsidiaries of U.S. multinationals in Canada, and Lipsey's (1978) observations regarding the reliability of the data for U.S. firms. More recently, Harrison, Love, and McMillian (2004) use D&B's cross-country foreign ownership information. Other research that has used D&B data includes Black and Strahan's (2002) study of entrepreneurial firm activity in the United States, and Acemoglu, Johnson, and Mitton's (2005) cross-country study of concentration and vertical integration.

[6] Dun & Bradstreet is a government-approved source for assigning SIC codes to companies. D&B uses the United States Government Department of Commerce, Office of Management and Budget, Standard Industrial Classification Manual 1987 edition to classify business establishments.

significant variation in international wealth and resource misallocation, precisely what we wanted for a study of development accounting.[7]

In most of the countries considered, our dataset provides highly satisfactory coverage. To give some sense, we compared our data with the Statistics of U.S. Businesses collected by the U.S. Census Bureau. The U.S. 2001-2002 business census records 7,200,770 "employer establishments" with total sales of $22 trillion. Our data include 4,293,886 establishments with more than one employee with total sales of $17 trillion. The U.S. census records 3.7 million small (fewer than 10 employees) employer establishments; our data include 3.2 million U.S. firms with more than one and fewer than 10 employees.

We also compare the U.S. owned subsidiaries in the WorldBase data with information on U.S. owned firms from the U.S. Bureau of Economic Analysis (see Figures 1a and 1b). The BEA's U.S. Direct Investment Abroad: Benchmark Survey, a confidential census conducted every five years, covers virtually the entire population of U.S. MNCs. Firm-level data is not readily available, but the BEA reports aggregate and industry level information. In 2004, the BEA reported sales (employment) by foreign affiliates of U.S. MNCs totaling $3,238 billion (10.02 million employees).[8] According to DNB data for 2005, the sum of all sales (employment) by foreign establishments reporting U.S. parents was $2,795 billion (10.07 million employees). Not only is the total similar, but the distribution across countries is also consistent. Figure 1a plots the total sales (by country) of the foreign affiliates of U.S. MNCs as reported in the BEA's Benchmark Survey 2004 against the total sales (by country) of all firms in the D&B data that reported a U.S. based parent.[9] The correlation is striking, suggesting that the cross-country

[7] The countries in the sample are Algeria, Argentina, Australia, Austria, Bangladesh, Belgium, Benin, Bolivia, Brazil, Cameroon, Canada, Chile, China, Colombia, Congo, Costa Rica, Denmark, Dominican Republic, Ecuador, Egypt, El Salvador, Ethiopia, Finland, France, Gambia, Ghana, Greece, Guatemala, Haiti, Honduras, India, Indonesia, Iran, Ireland, Israel, Italy, Jamaica, Japan, Jordan, Kenya, Korea, Malawi, Malaysia, Mali, Mauritius, Mexico, Mozambique, Netherlands, New Zealand, Nicaragua, Niger, Norway, Pakistan, Panama, Papua New Guinea, Paraguay, Peru, Philippines, Portugal, Romania, Rwanda, Senegal, Sierra Leone, Singapore, Spain, Sweden, Switzerland, Syria, Thailand, Togo, Trinidad & Tobago, Tunisia, Uganda, United Kingdom, Uruguay, USA, Venezuela, Zambia, Zimbabwe.

[8] See http://bea.gov/bea/di/usdop/all_affiliate_cntry.xls.

[9] http://bea.gov/bea/di/usdop/all_affiliate_cntry.xls.

distribution of multinational activity in the D&B data matches that found in the U.S. BEA's benchmark survey.[10]

Although we consider the WorldBase data to be highly informative with respect to the question we posed, we are nevertheless aware of its limitations. In our final sample, the number of observations per country ranges from more than 7 million firms in the United States to fewer than 20 firms in Malawi. That this variation reflects differences not only in country size, but also in the intensity with which Dun & Bradstreet samples firms in different countries, raises the concern that our measures of firm size might be affected by cross-country differences in the sample frame.

For example, in countries in which coverage is lower, more established, often older and larger, enterprises might be overrepresented in the sample, which could bias our results. In particular, we know that poorer countries typically have a sizeable informal sector populated by small firms (Schneider and Enste 2000). Because it probably does not capture most of the informal sector, the Dun & Bradstreet sample tends to underreport the number of smaller firms in poor countries. To address this concern, we slice the data in different ways and redo our calculations for many possible cases.

To mitigate the potential for bias resulting from not having small firms in poor countries represented, we truncate the data for all countries. In our benchmark exercise, we use only information for firms with at least 20 employees, but we also work with other thresholds to test the robustness of the results. Similarly, although in our benchmark exercise we use all countries for which there are more than 10 observations, which implies in a data set with 79 countries, we also work with sub-samples in which countries have large numbers of observations.[11]

We depict the main features of the dataset in Figures 2 to 5, in which we measure the size of a firm by the logarithm of its number of employees. Income per worker is from the Penn World Table version 6.1, and refers to PPP adjusted dollars. Figures 2, 3, and 4 plot, respectively, the mean, variance,

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[10] This is likely to be due to errors and differences in classification of subsidiaries as U.S. or not.

[11] We thank Daron Acemoglu for having pointed out this problem to us and Kei-Mu Yi and Mark Bils for suggesting this solution. An alternative solution would be to take a stand on the distribution function and artificially complete the sample for poor countries. The approach of cutting out the firms below a threshold is non-parametric and probably minimizes distortions.

and skewness of the firm size distributions of each country against income per worker (in logarithm). Note that mean size and variance size are negatively related to income, with correlations equal to -0.73 and -0.62, respectively (significant at the 1% level). Skewness, in contrast, is positively correlated with income (0.52, also significant at the 1% level). Figure 5 depicts the relation between mean size of the firm and size of the market, measured in terms of the number of employees (as reported in Penn World Table 6.1). Note that these two variables are not correlated (the correlation is equal to 0.02, which is not significant at the 5% level**)**.

3 Model

Our model draws heavily from Melitz (2003), Restuccia and Rogerson (2007), and Hsieh and Klenow (2007). Firm dynamics and policy distortions are as in Restuccia and Rogerson (2007), but we assume that firms have constant returns to scale technologies and some degree of market power, as in Hsieh and Klenow (2007). Because of the degree to which our model borrows from these previous works, we attempt to be as concise as possible.

Assume the final output is a C.E.S. aggregate of a continuum of differentiated goods, indexed by ω:

$$Y = \left(\int_{\omega \in \Omega} y_i^{\frac{\sigma - 1}{\sigma}} d\omega \right)^{\frac{\sigma}{\sigma - 1}} \tag{1}$$

where the measure of the set Ω represents the mass of available goods. This implies that the demand for good ω is given by

$$y_\omega = \frac{Y}{p_\omega^\sigma} \tag{2}$$

where p_ω denotes the price of good ω and the price of final output is normalized to one.

There exists a continuum of firms, each of which chooses to produce a different variety ω. Firms' technologies share the same Cobb-Douglas functional form, but might differ in their productivity factors, which are indexed by φ:

$$y_\varphi = AA_\varphi k_\varphi^\alpha l_\varphi^{1-\alpha} \tag{3}$$

where A is the economy-wide productivity factor, A_φ is the firm-specific productivity factor, k_φ and l_φ are, respectively, the capital rented and labor hired by such a firm, and α is the usual capital share parameter. Conditional on remaining in operation, an incumbent firm maximizes its period profit, which is given by

$$\pi_\varphi = (1-\tau_\varphi) p_\varphi y_\varphi - rk_\varphi - wl_\varphi \tag{4}$$

where τ_i denotes a firm specific output tax (or subsidy), and r and w denote the rental rates of capital and labor, respectively. Note that we assume taxes to be a function of a firm's productivity. Following Restuccia and Rogerson (2007), one should understand τ_i to be not literally a tax, but rather a general distortion.[12] Among the different types of policies that might generate these effects are non-competitive banking systems, product and labor market regulations, corruption, and trade restrictions.

Profit maximization, subject to the demand curve, implies the following expressions:

$$l_\varphi = \frac{y_\varphi}{AA_\varphi}\left(\frac{(1-\alpha)r}{\alpha w}\right)^\alpha \tag{5}$$

$$k_\varphi = \frac{y_\varphi}{AA_\varphi}\left(\frac{\alpha w}{(1-\alpha)r}\right)^{1-\alpha} \tag{6}$$

$$\frac{\left(p_\varphi - \dfrac{r^\alpha w^{1-\alpha}\left[(\frac{1-\alpha}{\alpha})^\alpha + (\frac{\alpha}{1-\alpha})^{1-\alpha}\right]}{(1-\tau_\varphi)AA_\varphi}\right)}{p_\varphi} = \frac{1}{\sigma} \tag{7}$$

[12] Restuccia and Rogerson (2007) study a class of distortions that occasions changes in neither aggregate prices nor aggregate factor accumulation. The authors examine policy distortions that have the direct effect of engendering heterogeneity in the prices to individual producers and reallocation of resources across plants. This feature leads the authors to refer to these distortions as *idiosyncratic* to emphasize that they might be different for each producer.

which correspond to the labor and capital allocation and pricing equation (Lerner's formula). Plugging the last expression back into demand (2) gives the amount produced by each firm,

$$y_\varphi = Y\left(\frac{(\sigma-1)(1-\tau_\varphi)AA_\varphi}{\sigma r^\alpha w^{1-\alpha}\left[(\frac{1-\alpha}{\alpha})^\alpha + (\frac{\alpha}{1-\alpha})^{1-\alpha}\right]}\right)^\sigma \tag{8}$$

The equilibrium will be characterized by a mass M of firms (and thus M goods) and a distribution μ_φ of firm productivity factors over a subset of $(0, \infty)$. In such equilibrium, the aggregate levels of capital and labor are given by $K = \int_0^\infty Mk_\varphi \mu_\varphi d\varphi$ and $L = \int_0^\infty Ml_\varphi \mu_\varphi d\varphi$. Plugging (8) into (6) and (7) yields expressions for K and H as functions of Y. Combining these expressions with (1) and (8), we obtain

$$Y = A\frac{\left[\int_0^\infty (1-\tau_\varphi)^{\sigma-1} A_\varphi^{\sigma-1} M \mu_\varphi d\varphi\right]^{\frac{\sigma}{\sigma-1}}}{\int_0^\infty (1-\tau_\varphi)^\sigma A_\varphi^{\sigma-1} M \mu_\varphi d\varphi} K^\alpha L^{1-\alpha} \tag{9}$$

This equation will constitute the backbone expression for our calculations. As we will see in the next section, it is not necessary to specify the rest of the economic environment to use this equation. We do so, however, to gain a better understanding of the interplay of the different effects of the hypothesis on the results.

Following Restuccia and Rogerson (2007), we consider the economy to be populated by an infinitely lived representative household with preferences over streams of consumption goods that does not care about leisure. There is also a large (unbounded) pool of firms prospectively entering the industry. To enter, however, incurs a cost; prospective entrants must make their entry decision knowing that they face a distribution of potential draws for A_φ (and thus τ_φ). Although a firm's productivity and tax remain constant over time, in any given period each firm faces a constant probability of death.

The steady-state equilibrium of this model is obtained as follows. As usual, the consumer problem determines the rental rate of capital, which is a function of the time discount factor and the capital depreciation rate. Given the rental rate of capital, the zero profit condition for entry of firms determines the steady-state wage rate. Labor supply is inelastic, and so, in equilibrium, total labor demand must be equal to one. It turns out that labor market clearing determines the equilibrium mass of firms.

4 Calibration

As noted above, our dataset consists of firm size histograms for each country. The fundamental step in our calibration is thus to find firm-specific tax distortion profiles that make each country's artificial economy firm size histogram match the data. That is, we must find the distortions profile that would make the histogram of the U.S. economy, which is presumably undistorted, the histogram of another country. To do this, we need to map the firms of each country to the firms of the U.S. economy, which involves dividing each country's histogram into a certain (large) number of cells denoted by N.[13] To achieve this mapping as simply and directly as possible, we make this division such that all countries' histograms have the same number of cells. We further give the cells of each histogram the same mass. As we shall see, however, calibration requires that across countries the cells have different masses.

Having completed the division of the histograms, we can begin to find firm specific productivity factors and taxes. Plugging equation (8) into equation (5) and comparing the resulting labor input for two different firms gives us

$$\frac{l_i}{l_j} = \frac{(1-\tau_i)^{\sigma} A_i^{\sigma-1}}{(1-\tau_j)^{\sigma} A_j^{\sigma-1}} \tag{10}$$

where i and j refer to two firms (i.e., two different cells of the histogram). As noted earlier, we assume the U.S. economy to be sufficiently undistorted to provide a good benchmark against which to assess firm specific productivities. More precisely, we assume $\tau_j = 0$ for all U.S. firms, and use the U.S. data to determine the A_j factors. We do this by normalizing $A_1 = 1$ and using equation (10) to determine A_i, for $i = 2, 3, \ldots, N$.

[13] Note that N denotes the number of cells and not the actual number of firms in the sample. For example, in the case N much bigger than the number of firms in the sample, there will be many cells for each firm. The relevant implication here is that we are capturing (at most) N moments of each distribution. Note also that the division of histograms into cells does not have any implication for the mass of firms in a country, which is denoted by M.

The next step is to find the distortions for each country, which we accomplish by mapping the histogram cells of each country to the U.S. histogram cells. This is done the natural way by sorting the histogram cells by number of employees (see Figure 6). The mapping between any two countries' histograms is thus such that the n^{th} smaller cell of one corresponds to the n^{th} smaller cell of the other. This approach engenders the *minimum distortion possible* to our economies, that is, tax distortions affect firm size but do not change the size ordering of a country's firms. In other words, distortions never result in more productive firms having fewer input factors than less productive firms.[14]

Returning to equation (10), we can use the previously determined A_i's to obtain τ_i as a function of τ_1, for $i = 2, 3, \ldots, N$, for each country. More precisely, using

$$(1-\tau_i^*) = (1-\tau_i)/(1-\tau_1) \tag{11}$$

we can obtain τ_i^* for $i = 1, 2, 3, \ldots, N$. Note that we do not need τ_1 to employ equation (9). If we plug equation (11) into equation (9), the terms on $(1 - \tau_1)$ in the numerator and the denominator cancel out, giving equation (9) with τ_i^* replacing τ_i.

To calibrate the mass of each country's firm distribution, we resort to the labor market clearing equation, $L = \int_0^\infty M l_\varphi \mu_\varphi d\varphi$. In practice, after the histogram divisions, and remembering that we are normalizing the labor force to unity, this becomes

$$M = N / \sum_{i=1}^{N} l_i \tag{12}$$

We borrow the technology parameters from the literature. As usual, we assume $\alpha = 1/3$. In our benchmark calibration, we set $\sigma = 6$. This parameter value delivers a 20% mark-up in price over marginal cost, which is in line with Rotemberg and Woodford (1992).

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[14] We can think of the mapping between histograms as an identification problem that requires some assumption. Restuccia and Rogerson (2007) analyze various alternatives including the case in which there is no correlation between distortion and firm size. The assumption adopted here has the property of minimizing distortion and thus underestimating the explanatory power of misallocation.

To relate our model to Caselli's (2005) calculations, we substitute labor for "quality adjusted" work force. With some abuse of notation, we rewrite equation (9) to include the human capital factor *h*:

$$Y = A\frac{\left[\sum_{i=1}^{N} M(1-\tau_i^*)^{\sigma-1} A_i^{\sigma-1}\right]^{\frac{\sigma}{\sigma-1}}}{\sum_{i=1}^{N} M(1-\tau_i^*)^{\sigma} A_i^{\sigma-1}} K^{\alpha}(Lh)^{1-\alpha} \tag{13}$$

We then follow Caselli (2005) in calibrating the remaining parameters, the values for *Y*, *K*, and *h,* for each country. Briefly, *Y* and *K* are from the 6.1 version of the Penn World Tables.[15] Capital is calculated by perpetual inventory method, with depreciation rate equal to 6% and the initial capital determined by the initial investment rate and its geometric growth over the period. Following Hall and Jones (1999), *h* is measured by the formula $h = \exp(\psi(s))$, where, following Barro and Lee (2001), ψ is piecewise linear and *s* denotes average number of years of schooling. We continue to normalize the size of the labor force to $L = 1$, as we evaluate output by number of workers.

An interesting aspect of the calibration is that it did not require that we specify many economy parameters, such as the household's preference discount factor, firms' entry costs, and the probability that a firm exits the market. Such specification would have been necessary to obtain a complete characterization of the equilibrium including determination of factor prices and tax distortions (i.e., τ_1). We would also have had to use the "free entry" condition, which was not required for our purposes.

For the purposes of this paper, the distribution of firms' size is a summary statistic of the resource misallocation for each country. That is, in order to employ the chosen model to determine cross-country income differences, we do not need to know entry costs or the probability that a firm dies, which presumably depends on the bankruptcy laws. But an analysis of these characteristics is probably essential for drawing explicit policy implications related to inter firm misallocation of resources.

[15] The 6.2 version, which will include data up to 2004, and in this sense is more compatible with the WorldBase dataset, is still incomplete as of February 2007.

5 Results

To perform the calibration, we make the number of cells, *N,* equal to 100,000. With that, the artificial histogram becomes a good approximation of the real data histogram even when firm size distribution is extremely skewed. We then obtain firm productivity for the United States, A_i (Figure 7), and for each country, the distortions τ_i (Figure 8).[16]

Figure 7 presents the U.S. firm size distribution, Figure 8 the type of distortion needed to transform the U.S. firm size distribution into another country's firm size distribution. Remember that τ_1, the distortion of the smallest firm, was normalized to zero for all countries. Thus, one should not understand τ_j to be indicative of the aggregate distortion. Rather, Figure 8 indicates, for each country, the magnitude of distortions over firms *relative to* the distortions over small firms.

Note the considerable variety in τ profiles. For some countries, τ is not monotonic in the size of the firm; for some countries it is positive, for others negative. The cloud of τ profiles also indicates that the "median" distortion corresponds to negative values for τ, which become more negative with firm size. That is, the most typical distortion corresponds to subsidies to big firms (or taxes to small firms) that increase (decrease) with the size of the firm.

After obtaining the distortions, we calculate the impact of resource misallocation on each country's productivity. Analogously to Caselli (2005), we make

$$y = ADk^{\alpha}h^{1-\alpha} \tag{14}$$

where $y = Y/L$ and $k = K/L$ are output per worker and capital per worker, respectively, and D is the misallocation factor, defined as

[16] Although we chose $N = 100{,}000$ for our calculations, due to graphical limitations, the figures depict the results for $N = 100$.

$$D \equiv \frac{\left[\sum_{i=1}^{N} M(1-\tau_i^*)^{\sigma-1} A_i^{\sigma-1}\right]^{\frac{\sigma}{\sigma-1}}}{\sum_{i=1}^{N} M(1-\tau_i)^{\sigma} A_i^{\sigma-1}} \tag{15}$$

To calculate the measure of the success of our exercise and compare to previous work, we define the *factor-only model*, y_{KH}, and the *misallocation model*, y_{DKH}, as, respectively,

$$y_{KH} \equiv k^{\alpha} h^{1-\alpha} \tag{16}$$

$$y_{DKH} = D k^{\alpha} h^{1-\alpha} \tag{17}$$

Our measure of success is based on the question: What would the dispersion of incomes be if all countries had the same A? That is, we define the measure of success of the factor-only model and misallocation model, respectively, as

$$success_{KH} \equiv \frac{Var[\log(y_{KH})]}{Var[\log(y)]} \tag{18}$$

$$success_{DKH} \equiv \frac{Var[\log(y_{DKH})]}{Var[\log(y)]} \tag{19}$$

Before analyzing the results of our benchmark experiment, summarized in Table 1, it is useful to check their consistency with Caselli's (2005) results. Because our sample contains 79 countries and his 94, the success of the factor-only model in our case is 0.417, slightly greater than the 0.385 obtained in his calculation. Analogous observations apply to each sub-sample of countries.

The first and foremost observation about the misallocation model is that it displays a success measure of 0.58. This figure, being about 40% higher than the corresponding figure for the factor-only model, indicates that dispersion of misallocation across countries is quantitatively an important additional factor to physical and human capital.

We further observe that the misallocation model displays high correlation with countries' income, equal to 0.95, as shown in Figure 9. In fact, the correlation between the misallocation factor D and countries' income (in logarithms) is equal to 0.54. That is, misallocation is not only adding noise to the model, it is contributing to our understanding of income differences.

The sub-samples of countries mostly yield conclusions that parallel those reached in Caselli's (2005) discussion of the factor-only model. Variation in log income per worker is higher in sub-samples that are, on average, poorer (non-OECD, Africa). Moreover, it is more difficult to explain precisely income differences in the sub-samples in which poor countries are involved, which is where a model is needed most. Unfortunately, as Table 1 indicates, the misallocation model does not help much in this dimension. Although it can fully account for the income variation of OECD countries, the misallocation model can only explain about half of the dispersion in the Non-OECD group.

For the Asia and Oceania subgroup, on the other hand, the misallocation model performs a lot better than the factor-only model. Importantly, this was not driven by a single country. Rather, the misallocation factor increased the dispersion of incomes in a homogeneous way, displaying a correlation with actual incomes of 0.93.

6 Robustness

We test the sensitivity of our results by conducting a series of robustness checks. Specifically, we change some of the model's hypotheses and slice the data in different ways. The main results are unchanged by these manipulations.

6.1 Sampling Intensity

Our benchmark experiment includes all countries with sample size greater than 10 observations (i.e., 10 firms). This enabled us to study a large group of countries, but might raise concerns about the reliability of the data and of the results for countries with fewer observations. We report here the results obtained when we select only countries with sample sizes greater than 100 firms, 1,000 firms, and 10,000 firms. Reducing the dataset in this way has two effects, (1) it restricts the sample to countries with higher sample intensity, and (2) it excludes countries in which Dun & Bradstreet collected little information. The latter tend to be poor countries, in which smaller firms tend to be underrepresented. Coincidently, these are the countries in which the dual market (black market) operates, making the collection of data more difficult. Remember, however, that knowing that this could bias our results, we truncated the data in the benchmark exercise.

Table 2 displays the results. Note that as we reduce the sample of countries, the misallocation model has similar performance. Although it improves for the sub-sample of more than 1,000 firms, its explanatory power returns to .58 for more restrictive (and reliable) datasets. We take from this that our original experiment is probably a good quantitative point of reference.

6.2 Elasticity of Substitution

In our benchmark experiment, we calibrate the elasticity of substitution as $\sigma = 6$. Although this is our preferred calibration, there is considerable uncertainty about this parameter. In this section, we redo the entire experiment using $\sigma = 3.8$ and $\sigma = 10$. The former figure was used by Bernard et al. (2003), and implies a 36% mark-up in price over marginal cost. The latter figure delivers an 11% mark-up, and is in line with Basu and Fernald's (1997) findings.

Table 3 presents the results for $\sigma = 3.8$. The first line of the table, which reports results for the entire sample, gives a favorable first impression. For this calibration, success increases to 0.755. Such a reading is, however, misleading. The sub-samples analysis indicates that the misallocation model tends to over-explain the data in many cases. This might be a consequence of the small number of observations in each sub-sample, or a problem with the data. But we believe it to be more reasonable to conclude that the problem is with the calibration. In our view, with $\sigma = 3.8$, the model overestimates the effect of misallocation.

Table 4 reports the results for $\sigma = 10$. For this calibration the misallocation model success is reduced to 0.500, and the sub-samples do not indicate any inconsistencies. The question here is whether this calibration is more adequate than our benchmark. Although it is hard to know for sure, casual observation suggests that industries in developing countries tend to be less competitive than in developed countries, and thus characterized by higher mark-ups. With this in mind, and given that $\sigma = 10$ was obtained for the U.S. economy, we think it is reasonable to consider the Table 4 results to be a lower bound for the actual success of the misallocation model.

6.3 Truncation

In the benchmark experiment, we truncate our dataset. The rationale for considering only firms larger than 20 employees was that differences in the intensity with which Dun & Bradstreet samples firms might be affected by cross-country differences and, thus, bias our results. Poorer countries typically have large, informal sectors characterized by small firms that might not be captured in the dataset. Consequently, the dataset might erroneously indicate, for example, a low mean for the firm size distribution in poor countries.

Of course, there is no clear indication of the correct threshold for truncating the data. The fact that the official agency in some countries (such as Netherlands) only collects data for firms with more than 20 employees suggests that this is a reasonable threshold. In any case, Tables 5 and 6 address this question by reporting the experiment results for the cases in which the threshold was 10 employees and 50 employees, respectively.

As expected, the results in Tables 5 and 6 are qualitatively the same as those in Table 1. From a quantitative point of view, these experiments indicate that the results are not very sensitive to the threshold. For a relatively large change in the threshold, the main success measure varied by less than 10 percent. Our view is that the benchmark results thus represent a good compass reading.

6.4 Multiple Sectors

Our benchmark experiment assumes the economy to have only one sector. In this subsection, we redo our experiment under the assumption that the economy has multiple sectors, as in Hsieh and Klenow (2007). Specifically, we assume that the final good is produced by combining the output Y_s of S manufacturing industries, according to a Cobb-Douglas technology thus:

$$Y = \prod_{s=1}^{S} Y_s^{\theta_s} \qquad \text{where} \quad \sum_{s=1}^{S} \theta_s = 1 \tag{20}$$

Expenditure minimization implies

$$P_s Y_s = \theta_s Y \tag{21}$$

where P_s denotes the price of industry s and the final good price which was normalized to 1. As before, each industry output is the aggregate of differentiated products

$$Y_s = \left(\int_{\omega \in \Omega_s} y_i^{\frac{\sigma-1}{\sigma}} d\omega \right)^{\frac{\sigma}{\sigma-1}} \tag{22}$$

where the measure of the set Ω_s represents the mass of available goods in sector s. There is a continuum of firms, each of which chooses to produce a different variety ω. Again, these firms share the same Cobb-Douglas technology functional form, but might differ in their productivity factors (as in equation (3)) and maximize profits facing a firm-specific output distortion (as in equation (4)).

To address misallocation distortion in this environment, we calculate the factor D as

$$D \equiv \prod_{s=1}^{S} \left\{ \frac{\left[\sum_{i=1}^{N_s} M_s (1-\tau_i^*)^{\sigma-1} A_i^{\sigma-1} \right]^{\frac{\sigma}{\sigma-1}}}{\sum_{i=1}^{N_s} M_s (1-\tau_i)^{\sigma} A_i^{\sigma-1}} \right\}^{\theta_s} \tag{23}$$

Effectively, as in Hsieh and Klenow (2007), we make the misallocation factor equal to the weighted geometric average of the misallocation factor in each industry s.

Note that this way of calculating the misallocation factor considers only the misallocation that occurs *within* each sector. It does not consider the eventual misallocation of resources that makes sectors smaller or larger than their efficient size. A reason for calculating misallocation this way is that countries might specialize in sectors in which they have comparative advantage. In this case, they could have sectors with sizes that are different from those of the U.S. economy (our benchmark) and nevertheless be efficient. In any case, it is noteworthy that calculating distortions this way yields a lower bound of misallocation.

To implement this exercise, we restrict our attention to countries for which we have at least 10 observations (i.e., 10 firms) in at least 30 sectors, sector here referring to a two-digit SIC industry. This leaves a sub-sample of 32 countries. The choice of 30 sectors is arbitrary, but turns out to be a reasonable compromise between a large number of sectors and a large number of countries.

As before, the calibration methodology consists of matching model distributions to actual histograms, but now this is done for each sector of each country. The U.S. economy is again taken as a benchmark, and we find the distortion profiles for other countries. To obtain θ_s, the share of each sector in the economy, we use data on firm revenues for the U.S. economy, also from the WorldBase dataset and equation (21).

The results are presented in Table 4, which compares the success measures for the one sector and multiple sector economies for the same sub-sample of countries. The success of the factor-only economy is the same in both cases, as this model always contains only one sector. The success of the misallocation model is comparable in both specifications. Success is smaller in the multiple sector model, but this is probably a consequence of the way it was formulated. This can be seen as another indication of the robustness of the results.

Another interesting observation with regard to the multiple sector experiment is its relationship to Hsieh and Klenow's (2007) experiment. Their hypothetical "liberalizations" in China and India consider the elimination of various intra sector distortions such that capital and labor are hypothetically reallocated to equalize marginal products to the extent observed in the United States. Although they employ a different dataset and calibration than we use, that the experiments share the same general framework invites comparison.

Hsieh and Klenow (2007) find the gains from reallocating resources to be on the order of 25%-40% in China and 50%-60% in India. According to our calculations, in the multiple sector experiments, the gains for India and China are 31% and 35%, respectively. In the one sector experiments, these gains are, respectively, 41% and 62%. That our results seem to be fairly consistent with theirs is a final reassuring sign of the robustness of our experiments.

7 Conclusions

We calculated the implicit distortion needed to generate firm-size distributions consistent with firm-size histograms for a sample of 79 countries. We found the loss in output caused by these distortions to be quantitatively important. When added to differences in resources (human and physical capital), differences in misallocation of resources add about 40% to the explanatory power of our model of dispersion in cross-country income per worker. This result seems to be robust to changes in parameter calibrations and in the sub-samples in which the data are more reliable (rich countries).

One potential improvement to our analysis would be to make use of richer datasets. In particular, with a dataset that also contained information on revenues and capital per firm, one could employ a richer model with many distortions, as in Hsieh and Klenow (2007). In the present case, it is possible that one distortion could cancel out or add to the effect of another distortion, thus affecting total misallocation. The work of Bartelsman, Haltiwanger, and Scarpetta (2006) is an exciting step in this direction.

There is also potential for improvements in the theoretical framework. Following the literature, we use the United States as an undistorted benchmark from which we derive other countries' distortions. An alternative approach would be to calibrate the distortions observed in the United States, and obtain the characteristics of a truly undistorted economy to be used as a benchmark. This approach would require more modeling structure and assumptions. We pursue this line of research in future work.

Related to this last point, our exercise assumed that all countries share the same distribution of firm specific productivities as the United States, that is, that firm productivities are not correlated with firm distortions. In contrast, richer models of firm dynamics, such as that developed by Ericson and Pakes (1995), consider firms' development to be associated with "active learning." In such models, a firm's productivity tends to be connected to the distortion it faces. That is, distortions might lead a firm to invest more or less in R&D, which, in turn, would determine its productivity. As a consequence, the effects of misallocation might be different from those calculated here.

Another modeling issue worth exploring concerns the amount of competition among firms in an industry. Our model assumes that firms face a symmetric and constant elasticity of substitution that exogenously determines equilibrium mark-ups. A richer specification could endogenously determine the distribution of mark-ups and capture the impact of firms' entry costs on the degree of concentration in industries.

Finally, research should also shed light on how particular sources of inefficiency, such as credit market imperfections, macroeconomic volatility, defective bankruptcy procedures, or a malfunctioning regulatory environment, are driving cross-country differences in firm size distribution. This would be fruitful for drawing explicit policy implications. We leave this task to future work.

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Table 1: Success in Benchmark Experiment

Sub-sample	Obs.	Var[log(y)]	Var[log(y_{KH})]	Var[log(y_{DKH})]	Success$_{KH}$	Success$_{DKH}$
All	79	1.26	.52	.73	.42	.58
OECD	22	.047	.030	.049	.65	1.0
Non-OECD	57	.91	.36	.47	.39	.52
Africa	22	.75	.25	.27	.33	.36
Americas	23	.39	.20	.32	.50	.82
Asia and Oceania	18	.64	.32	.59	.49	.91
Europe	16	.16	.036	.061	.23	.40

Table 2: Success in More Reliable Sub-samples

Sub-sample	Obs.	Var[log(y)]	Var[log(y_{KH})]	Var[log(y_{DKH})]	Success$_{KH}$	Success$_{DKH}$
Above 10 firms	79	1.26	.53	.72	.42	.58
Above 100 firms	65	.97	.41	.58	.42	.60
Above 1,000 firms	41	.44	.18	.32	.41	.73
Above 10,000 firms	27	.23	.087	.13	.38	.58

Table 3: Success in Experiment with Elasticity of Substitution σ = 3.8

Sub-sample	Obs.	Var[log(y)]	Var[log(y_{KH})]	Var[log(y_{DKH})]	Success_{KH}	Success_{DKH}
All	79	1.26	.52	.95	.42	.75
OECD	22	.047	.030	.086	.65	1.8
Non-OECD	57	.91	.36	.61	.39	.68
Africa	22	.75	.25	.32	.33	.42
Americas	23	.39	.20	.46	.50	1.16
Asia and Oceania	18	.64	.32	.87	.49	1.35
Europe	16	.16	.036	.11	.23	.70

Table 4: Success in Experiment with Elasticity of Substitution σ = 10

Sub-sample	Obs.	Var[log(y)]	Var[log(y_{KH})]	Var[log(y_{DKH})]	Success_{KH}	Success_{DKH}
All	79	1.26	.52	.63	.42	.50
OECD	22	.047	.030	.037	.65	.78
Non-OECD	57	.91	.36	.41	.39	.46
Africa	22	.75	.25	.25	.33	.34
Americas	23	.39	.20	.26	.50	.66
Asia and Oceania	18	.64	.32	.45	.49	.70
Europe	16	.16	.036	.044	.23	.29

Table 5: Success in Experiment with Minimum Firm Size Equal to 10 Employees

Sub-sample	Obs.	Var[log(y)]	Var[log(y_{KH})]	Var[log(y_{DKH})]	Success_{KH}	Success_{DKH}
All	79	1.26	.52	.78	.42	.62
OECD	22	.047	.030	.056	.65	1.2
Non-OECD	57	.91	.36	.49	.39	.54
Africa	22	.75	.25	.27	.33	.36
Americas	23	.39	.20	.34	.50	.86
Asia and Oceania	18	.64	.32	.63	.49	.98
Europe	16	.16	.036	.073	.23	.48

Table 6: Success in Experiment with Minimum Firm Size Equal to 50 Employees

Sub-sample	Obs.	Var[log(y)]	Var[log(y_{KH})]	Var[log(y_{DKH})]	Success_{KH}	Success_{DKH}
All	79	1.26	.52	.67	.42	.53
OECD	22	.047	.030	.049	.65	1.0
Non-OECD	57	.91	.36	.45	.39	.50
Africa	22	.75	.25	.26	.33	.35
Americas	23	.39	.20	.30	.50	.75
Asia and Oceania	18	.64	.32	.52	.49	.81
Europe	16	.16	.036	.058	.23	.37

Table 7: Success in Experiment with Many Sectors

Experiment	Obs.	Var[log(y)]	Var[log(y_{KH})]	Var[log(y_{DKH})]	Success_{KH}	Success_{DKH}
One sector	32	0.41	.14	.23	.33	.55
Multiple sectors	32	0.41	.14	.19	.33	.46

Figure 1: Comparison U.S. Multinationals — BEA versus Dun and Bradstreet

Figure 1a: Sales of U.S. Multinationals

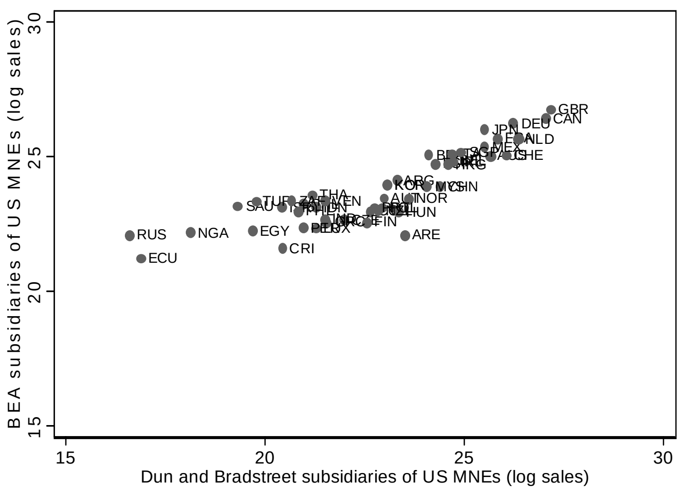

Figure 1b: Number of U.S. Subsidiaries

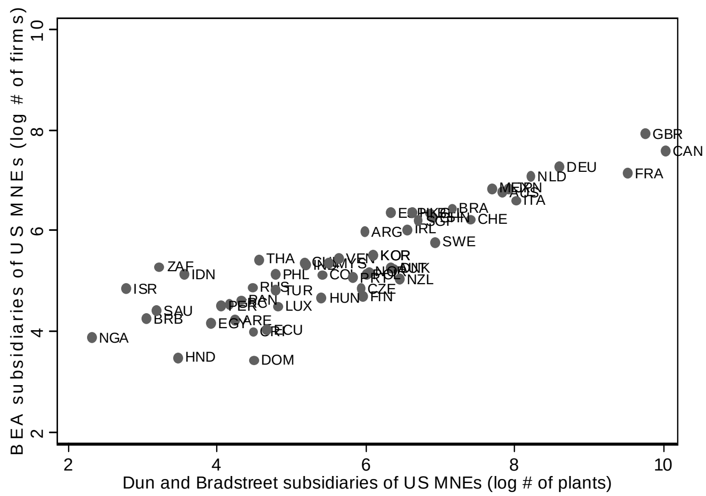

Figure 2: Mean of Firm Size against Income per Worker

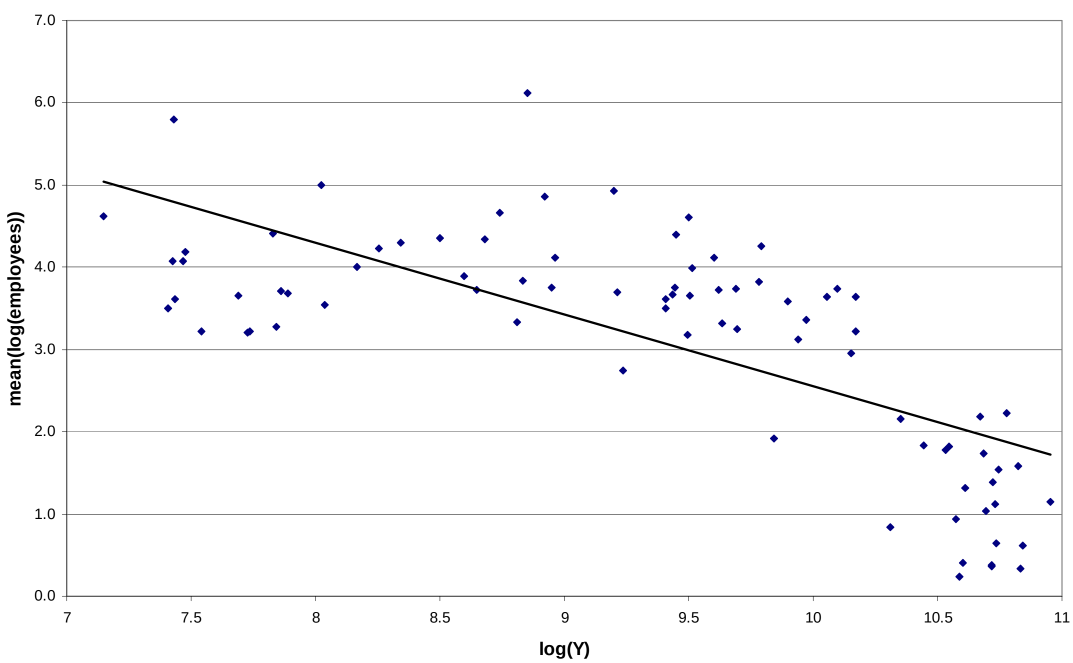

Figure 3: Variance in Firm Size against Income per Worker

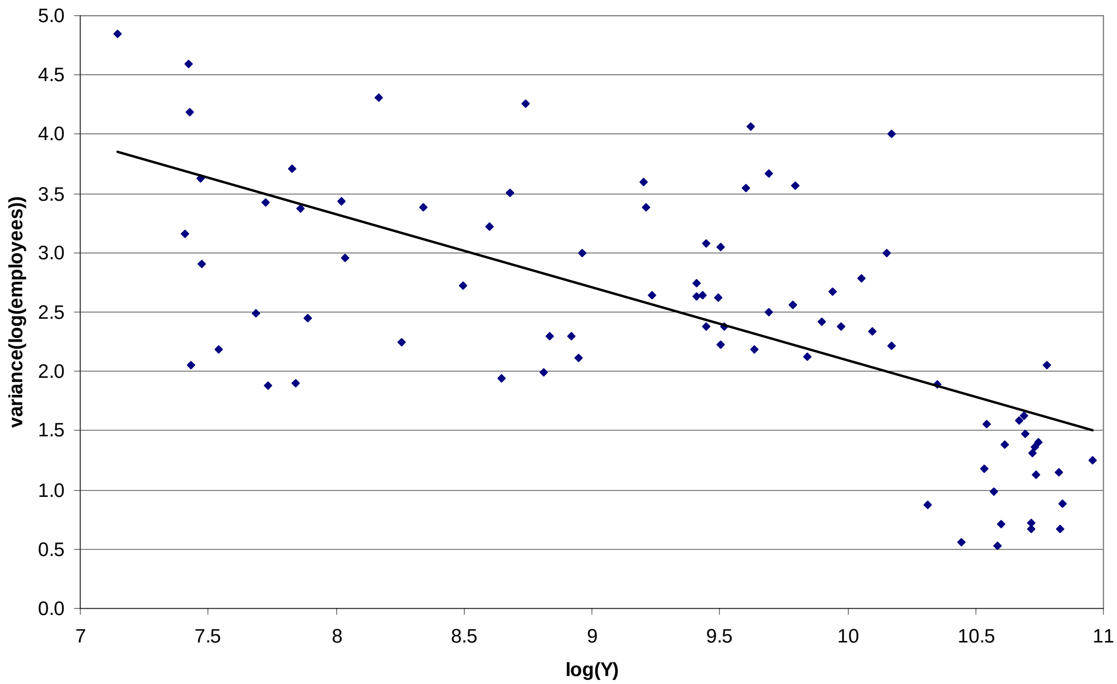

Figure 4: Skewness of the Firm Size Distribution against Income per Worker

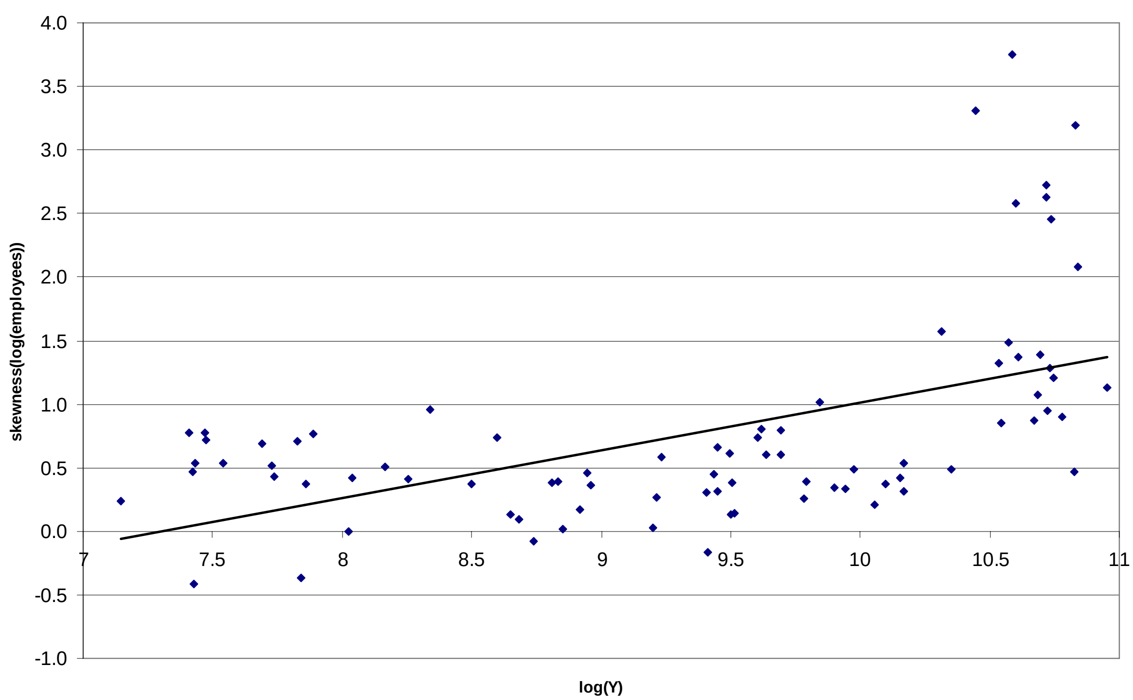

Figure 5: Mean of Firm Size against Market Size

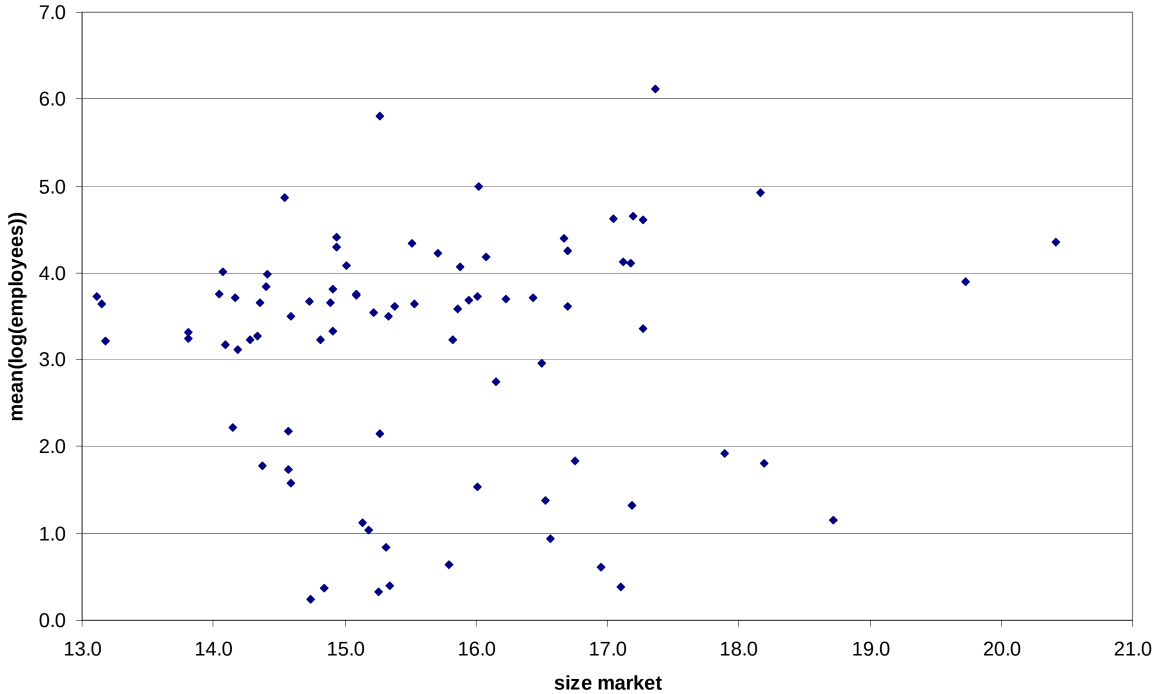

Figure 6: Histograms

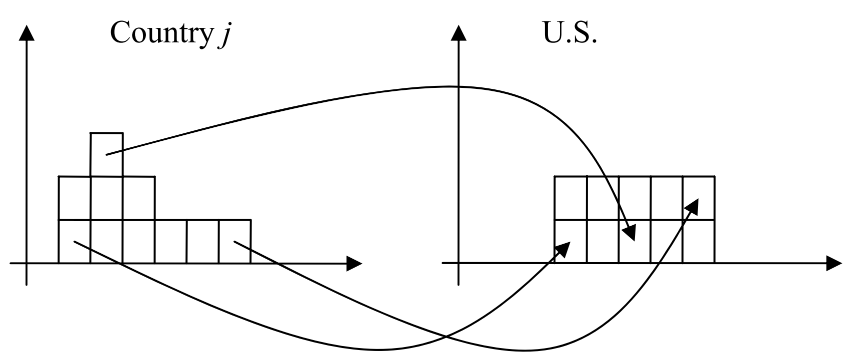

Figure 7: Firms' Productivities

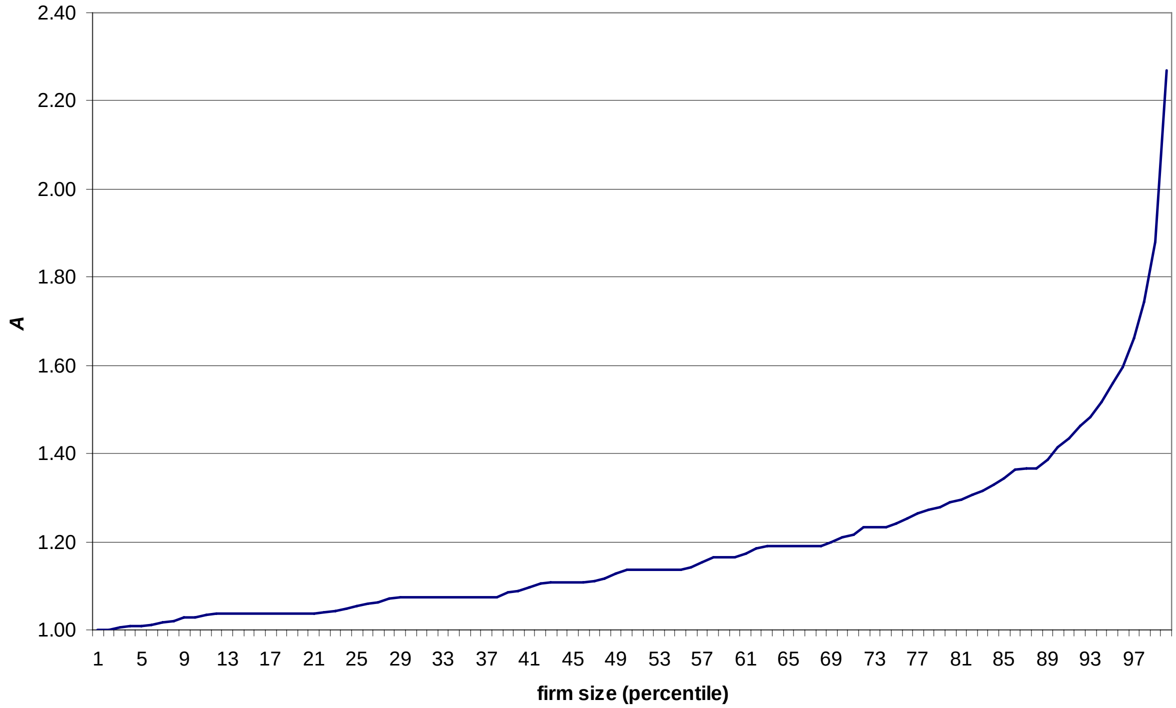

Figure 8: Tax Distortions for Various Countries

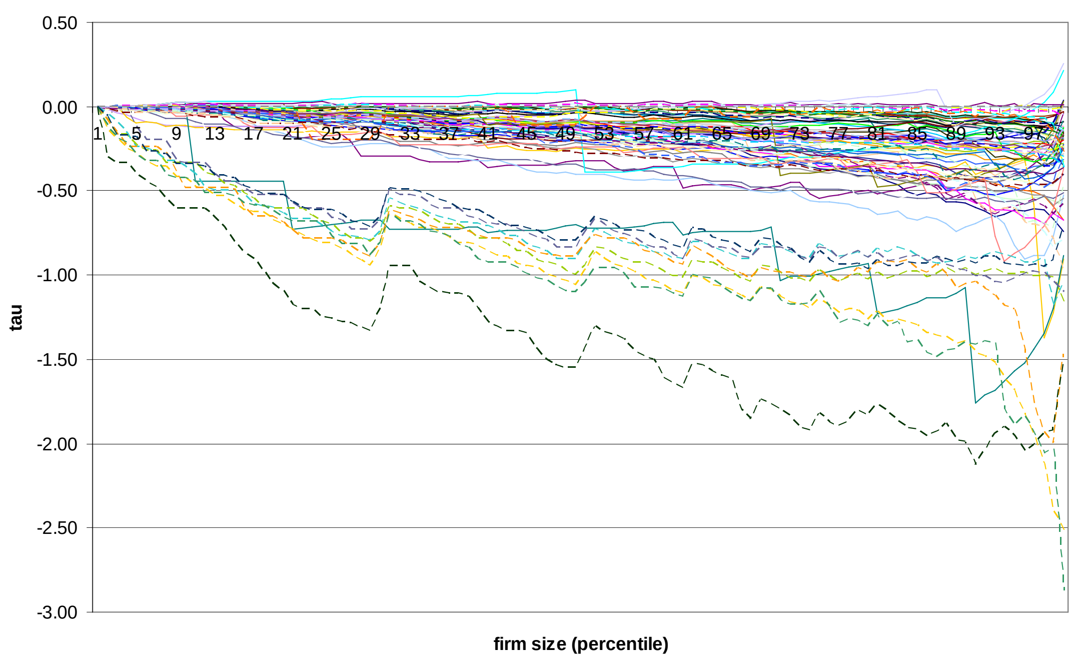

Figure 9: Misallocation Model against Income per Worker