Firm-Size Distribution and Cross-Country Income Differences

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Abstract

We investigate, using a unique firm level dataset of nearly 20 million firms in 80 countries, whether differences in the allocation of resources across heterogeneous plants are a significant determinant of cross-country differences in income per worker. Using a monopolistic competitive firm framework to derive our benchmark calibration, we find that the model over-explains income variance. We further explore whether the results are driven by sample biases, calibration assumptions, or modeling choice. We find the same results prevail even in sub-samples in which the data are more reliable, and when we vary the calibration assumptions. This suggests the need for more complex modeling structures. Despite these acknowledged shortcomings, our results suggest that misallocation of resources is a crucial determinant of income dispersion.

JEL classification: O1.
Key words: heterogeneous plants, productivity, policy distortions

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 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 (2006) 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 data set of more than 20 million firms in nearly 80 developing and industrialized countries. Specifically, we develop a simple model of firm dynamics that draws heavily upon previous work (Melitz 2003, Hsieh and Klenow 2006) and calibrate it to match our data set. 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 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 the 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

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[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 (2000).
[3] In particular, Restuccia and Rogerson (2007), using data for the United States, and Hsieh and Klenow (2006) using data for China and India, have found that resource misallocation can lower TFP.

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. In fact, for our benchmark calibration, the model *over-explains* cross-country income dispersion. This excessive power is, of course, undesirable, suggesting the possibility of problems with the data and/or the theoretical experiment. In particular, there might be issues with (i) data, (ii) parameter calibration, and (iii) modeling choice.

Various exercises and robustness tests performed in an attempt to understand the nature of our results reveal the problem to be most severe in the sub-samples for which the data are most reliable. In particular, our exercise tends to over-explain the data most for sub-samples of the richest countries, for which the data are more representative and trustworthy. We also find that the results are not particularly driven by the parameter calibration. These results suggest that more sophisticated modeling of firm dynamics might be essential to understanding the effects of resource misallocation.[4] We conclude with a discussion of the limitations of, and possible extensions to, our exercise. The acknowledged shortcomings notwithstanding, our results suggest that future research might find misallocation of resources to be 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 the 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 data from the Chinese and Indian manufacturing census 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 their marginal products, the authors find TFP gains on the order of a factor of 2. When performing an analogous exercise those two countries using our data we obtain 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

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[4] Our model assumes that firm productivities are not correlated with firm distortions. In contrast, in "active learning" models such as that developed by Ericson and Pakes (1995) a firm's productivity tends to respond to the distortion it faces and hence the effects of misallocation might be lower than calculated here. See section 7 for further discussion.

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 is a tentative conclusion.

2 Data Description

Cross-country empirical investigations at the firm level are notoriously difficult because of lack of data and problems with the few datasets that are available.[5] 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.

For the study reported here, we used data from Dun and Bradstreet's WorldBase, a database of public and private companies in 118 countries. WorldBase reports for each firm the number of employees, age of the firm, and the four-digit SIC-1987 code of the primary industry in which the firm operates. It also reports sales for firms in the most developed countries. The data are compiled from a number of sources—including partner firms in dozens of countries, telephone directory records, websites, and self-registration—with a view to providing clients with contact details and basic operating information about potential customers, competitors, and suppliers. All information is verified centrally via a variety of manual and automated checks. Information from local insolvency authorities and merger and acquisition records are used to track changes in ownership and operations.

The main advantage of our database is its size. Our original sample included nearly 24 million private firms in 2003/2004. Excluding territories with fewer than 10 observations and those for which the Penn Table 6.1 provides no data left us with observations in 80 countries, which exhibited significant variation in international wealth and resource misallocation, precisely what we wanted for a study of development accounting.

In most of the countries considered, our dataset shows a very 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.

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[5] 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.

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 not only differences in country size, but also differences 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. We address this concern in a number of ways, as by slicing the data in different ways and redoing our calculations for a sub-sample of countries with a large number of observations.

We depict the main features of the dataset in Figures 1 to 4, 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 1, 2, and 3 plot, respectively, the mean, variance, and skewness of 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 -0.72 and -0.60, respectively (significant at the 1% level). Skewness, in contrast, is positively correlated with income (0.53, also significant at the 1% level). Figure 4 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 0.03, which is not significant at the 5% level). Taken together, the features of our data are broadly consistent with those of the data used by Bartelsman, Haltiwanger and Scarpetta (2005, 2006).

3 Model

Our model draws heavily from Melitz (2003), Restuccia and Rogerson (2007), and Hsieh and Klenow (2006). 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 (2006). 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 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. 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.[6] 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:

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

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

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

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[6] Restuccia and Rogerson (2007) study a class of distortions that occasion 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,

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

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

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

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. 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 as 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 $i = 2, 3, \ldots, N$.

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 5). The mapping between any two countries' histograms is thus such that the nth smaller cell of one corresponds to the nth 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.

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, $L = \int_0^\infty Ml_\varphi \mu_\varphi d\varphi$. 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 use the value of σ from Bernard, Eaton, Jensen and Kortum (2003) and set $\sigma = 3.8$, which was calibrated to fit U.S. plant and macro trade data. This value for σ implies, in steady state, mark-ups too high relative to the evidence. But as Ghironi and Melitz (2005) argue, in a model with entry costs the free entry condition ensures that, on average, firms earn zero profits net of the entry costs.

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.[7] 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 the average number of years of schooling. We continue to normalize the size of the labor force to $L = 1$, as we evaluate output by the number of workers.

An important aspect of the calibration is that it did not require that we specify many economy parameters such as the household's preference discount factor, the firms' entry costs, and the probability that a firm exits the market. This specification would have been necessary to obtain a

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

complete characterization of the equilibrium including the determination of factor prices and tax distortions (i.e., τ_1). In this case, we would also have had to use the "free entry" condition, which was not required for our purposes.

What is interesting about this are the implicit implications of the modeling choice. For example, the chosen model does not require that we know entry costs to determine cross-country income differences. Similarly, the probability that a firm dies, which presumably depends on its scrap value and the bankruptcy laws, has no direct implications for country wealth. We interpret this observation to be a preliminary signal that the industry model we used, however simple and natural a choice, might have important limitations. In particular, one might have to employ more sophisticated models of industry dynamics to draw explicit policy implications. Likewise, it might be the case that the model's representation of firm dynamics is too simplistic to provide precise measurements of the effects of misallocation.

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 6), and, for each country, the distortions τ_i (Figure 7).[8]

Figure 6 presents the U.S. firm size distribution, Figure 7 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 7 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

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

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

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

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

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

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

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

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 80 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, in contrast to the factor-only model, it displays a success measure greater than 1, which is to say, the misallocation model over-explains the cross-country income dispersion. This, of course, should not be seen as a good result. It means that if all the countries had the same productivity, income differences would be higher than we actually see. In other words, it means that in order to observe the actual income differences, countries productivities (A) need to be negatively correlated with the part explained by the model (y_{DKH}).

We expand this last observation to include that the misallocation model displays high correlation with countries' income (equal to 0.91). In fact, the correlation between the misallocation factor D and countries' income (in logarithms) is equal to 0.70, as shown in Figure 8. That is,

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misallocation is not only adding noise to the model, it is contributing to our understanding of income differences, but excessively so.

The sub-samples of countries yield conclusions that parallel those reached in Caselli's discussion of the factor-only model. Variation in log income per worker is higher in sub-samples that are, on average, poorer (below the median, Non-OECD, Africa). Moreover, it is more difficult to explain income differences precisely in the sub-samples in which poor countries are involved, which is where the model is needed most. The misallocation model tends to over-explain even more the data for the sub-samples in which richer countries are involved.

Europe offers an interesting comparison between the factor-only and misallocation models. The extremely high human capital level of the lone Eastern European country (Romania) makes it quite difficult for the factor-only model to explain its low income. The misallocation model, on the other hand, easily explains Romania's low income, in fact, over-explains it by about 20%.

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, but the main results remain unchanged.

6.1 Dataset: 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 when we select only countries with sample sizes greater than 100 firms, 1,000 firms, 10,000 firms, and 100,000 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. Unfortunately, these are also the countries we care most about, as they are the ones with the highest income differences.

Table 2 displays the results. Notice that as we reduce the sample of countries, the misallocation model tends to over-explain even more the income variance. We saw this already in Table 1, which reported the results for the sub-samples with richer countries. The natural conclusion to

be drawn from this robustness test is that the problem is not in the data. Rather, the problem of excessive explanation persists and is amplified precisely when the data are more consistent and reliable.[9]

6.2 Calibration Parameters: Elasticity of Substitution

In our benchmark experiment, we calibrated the elasticity of substitution as $\sigma = 3.8$. Although this is our preferred calibration, there is surely a good amount of uncertainty about this parameter. In this section, we redo the entire experiment using $\sigma = 6$. This parameter value delivers a 20% mark-up in price over marginal cost, which is in line with Rotemberg and Woodford (1992).

The results are presented in Table 3. The first line of the table, which reports results for the entire sample, gives a favorable first impression. In this new calibration, success becomes 0.800 and the misallocation factor informs the data without over-explaining it. Such a reading is, however, misleading.

When we look at the sub-samples, we have the same problem as before: the experiment again over-explains income variance in the richest countries. It is true that now the mistake of over-explaining variance is smaller, but so is the success of explaining it in the poorest countries.[10] Interestingly, when we look at the results by continent we find that the experiment over-explains income dispersion only in Asia and Oceania. Although this might be a consequence of the small number of observations in each sub-sample, we believe it is more reasonable to conclude that the results with $\sigma = 6$ yield the same conclusions as the benchmark experiment.

6.3 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 (2006). 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.

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

Expenditure minimization implies

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

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[9] As we explain later, when we compare our analysis with that reported in the literature we obtain similar results, further easing concerns that the results might be driven by sampling biases.

[10] The same would happen if we used $\sigma = 10$, which is more in line with Basu and Fernald's (1997) findings.

where P_s denotes the price of industry s and the price final good 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 choosing 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 (2006), 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 to calculate 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 different from those of the U.S. economy (our benchmark) and nevertheless be efficient. In any case, it is noteworthy that calculating misallocation in 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, each 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 misallocation model over-explains income dispersion in both specifications. Success is smaller in the multiple sector model, but this is probably a consequence of the way it was formulated.

It is interesting to observe with regard to the multiple sector experiment its relationship to the experiment of Hsieh and Klenow (2006), whose hypothetical "liberalizations" in China and India consider the elimination of various intra sector distortions and employ a different dataset and calibration than are used in our study. The two experiments nevertheless share the same general framework, which invites a comparison. Hsieh and Klenow (2006) find the gains from reallocating resources to be on the order of 2 for both countries. According to our calculations, the gains for India and China are 2.08 and 2.06, respectively. That our results seem to be highly consistent with theirs is a reassuring sign of the quality of our dataset.

7 Discussion

We discuss here other assumptions that might affect our results.

In terms of the production function, we assumed the same technology parameters across countries, that is, the same labor and capital share. Work by Gollin (2002) suggests this to be a reasonable assumption as most countries have similar labor shares close to 2/3. But in any case, the nature of our exercise is to study precisely the contribution of differences in firm size distribution in accounting for TFP differences not the contribution of differences in the labor share. There might be additional issues related to using the same production structure across countries and industries and not using firm level deflators, but there are important data limitations in this regard. In addition, we use the United States as a benchmark in order to compare with the literature, but it is unclear whether any other country might better serve in this capacity.[11]

We believe it is more likely that our results are a consequence of the model we chose, specifically, the model's assumption 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

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[11] An alternative approach would be to calibrate the distortions observed in the U.S., and obtain the characteristics of a truly undistorted economy, to be used as a benchmark. This approach, however, would require a lot more modeling structure and assumptions.

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, determines its productivity. As a consequence, the effects of misallocation might be lower than 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.

Overall, our view is that more sophisticated models might be needed to properly calculate the effects of resource misallocation on income dispersion. Such models might 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.

8 Conclusions

We calculated the implicit distortion needed to generate firm-size distributions consistent with firm-size histograms for a sample of 80 countries. We found the loss in output caused by these distortions to be quantitative important. When added to differences in resources (human and physical capital), differences in misallocation of resources tend to over-explain the observed dispersion in cross-country income per worker. This result seems to be robust to changes in parameter calibrations, and is even more pervasive in the sub-samples in which the data are more reliable (rich countries). What went wrong with our experiment?

One natural possibility is that the Worldbase dataset is seriously flawed. It is always possible that some strong and unexpected bias inherent in these data is responsible for our results. It is also possible that a problem arises from the fact that this dataset contains (complete) information only about firm size distribution as measured by number of employees. If the dataset also contained information on revenues and capital per firm, one could employ a richer model with many distortions as in Hsieh and Klenow (2006). In this case, it is possible that one distortion could cancel out the effect of another distortion thus reducing total misallocation. To address such questions, future research should make use of datasets that might cover fewer countries but contain richer information for each, such as that compiled by Bartelsman, Haltiwanger and Scarpetta (2005).

We believe it is more likely that our results are a consequence of the model we chose. Although the model we applied is a natural first choice, it might be an excessively simplified representation of firm dynamics. We believe that adopting richer industry models might support more accurate and sensible calculations of the misallocation effects over income dispersion. Additionally, these models might be more suitable for drawing explicit policy implications. We leave this task to future research.

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Table 1: Success in Benchmark Experiment

Sub-sample	Obs.	$\text{Var}[\log(y)]$	$\text{Var}[\log(y_{KH})]$	$\text{Var}[\log(y_{DKH})]$	Success_{KH}	Success_{DKH}
All	80	1.243	.518	1.533	.417	1.233
Above the median	40	.193	.132	.801	.680	4.138
Below the median	40	.574	.271	.485	.472	.845
OECD	23	.090	.055	.413	.601	4.581
Non-OECD	57	.907	.357	.703	.393	.775
Africa	22	.753	.252	.329	.334	.437
Americas	23	.394	.197	.639	.500	1.623
Asia and Oceania	19	.608	.299	1.289	.492	2.120
Europe	16	.155	.036	.299	.233	1.933

Table 2: Success in More Reliable Sub-samples

Sub-sample	Obs.	$\text{Var}[\log(y)]$	$\text{Var}[\log(y_{KH})]$	$\text{Var}[\log(y_{DKH})]$	Success_{KH}	Success_{DKH}
Above 10 firms	80	1.243	.518	.994	.417	.800
Above 100 firms	66	.955	.402	1.328	.421	1.391
Above 1,000 firms	42	.433	.180	1.013	.415	2.341
Above 10,000 firms	27	.229	.087	.427	.378	1.864
Above 100,000 firms	18	.060	.049	.176	.807	2.911

Table 3: Success in Experiment with Elasticity of Substitution σ = 6

Sub-sample	Obs.	Var[log(y)]	Var[log(y_{KH})]	Var[log(y_{DKH})]	Success$_{KH}$	Success$_{DKH}$
All	80	1.243	.518	.994	.417	.800
Above the median	40	.193	.132	.424	.680	2.191
Below the median	40	.574	.271	.358	.472	.624
OECD	23	.090	.055	.200	.601	2.217
Non-OECD	57	.907	.357	.517	.393	.569
Africa	22	.753	.252	.271	.334	.360
Americas	23	.394	.197	.407	.500	1.033
Asia and Oceania	19	.608	.299	.761	.492	1.251
Europe	16	.155	.036	.134	.233	.863

Table 4: 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	0.413	.143	.773	.346	1.871
Multiple sectors	32	0.413	.143	.591	.346	1.430

Figure 1: Mean of Firm Size against Income per Worker
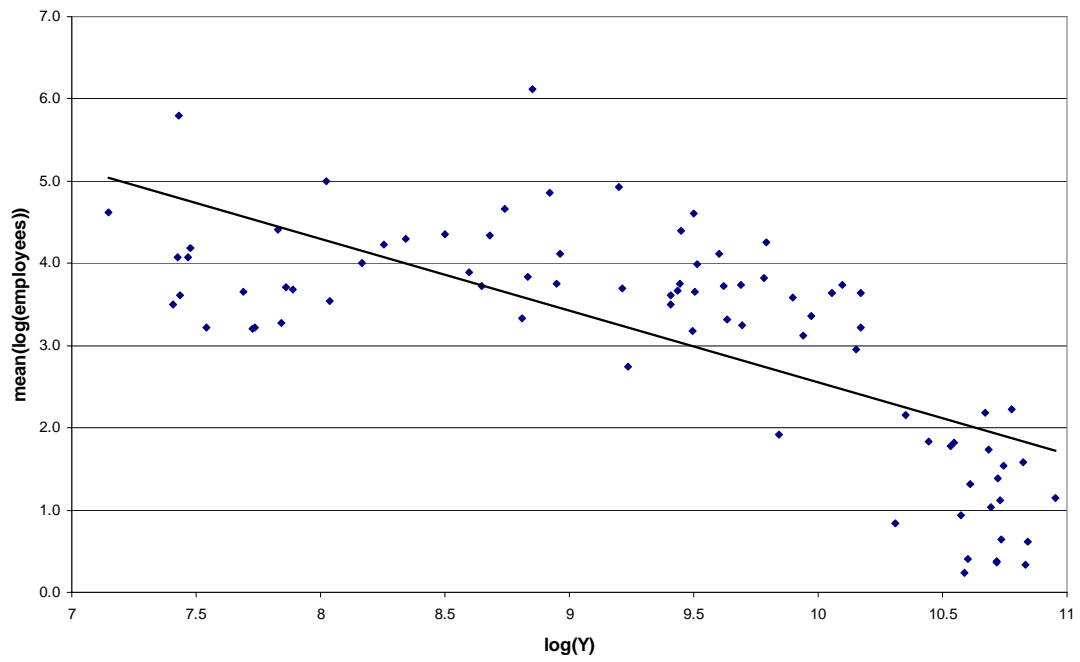
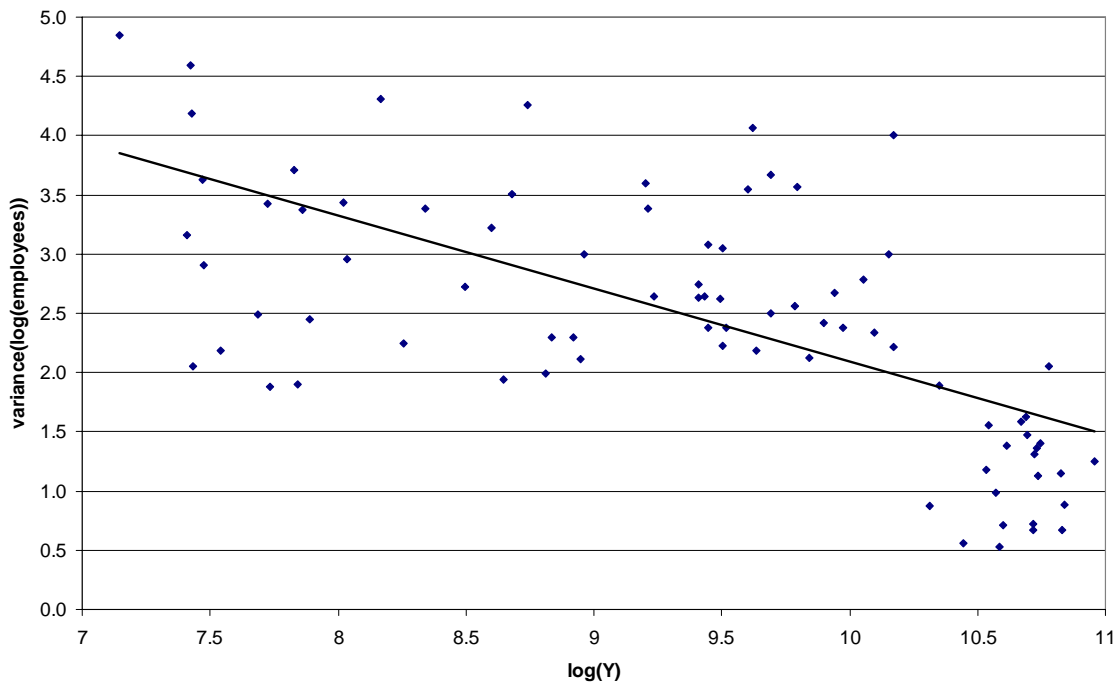Figure 2: Varianst in Firm Size against Income per Worker

Figure 3: Skewness of the Firm Size Distribution against Income per Worker
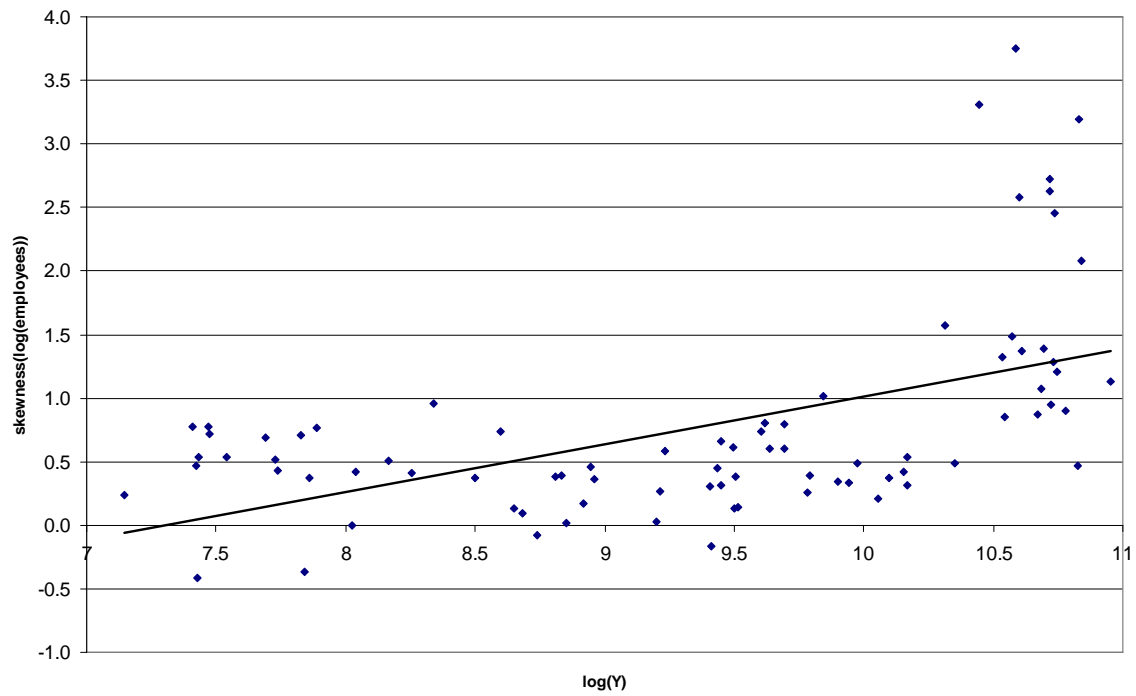

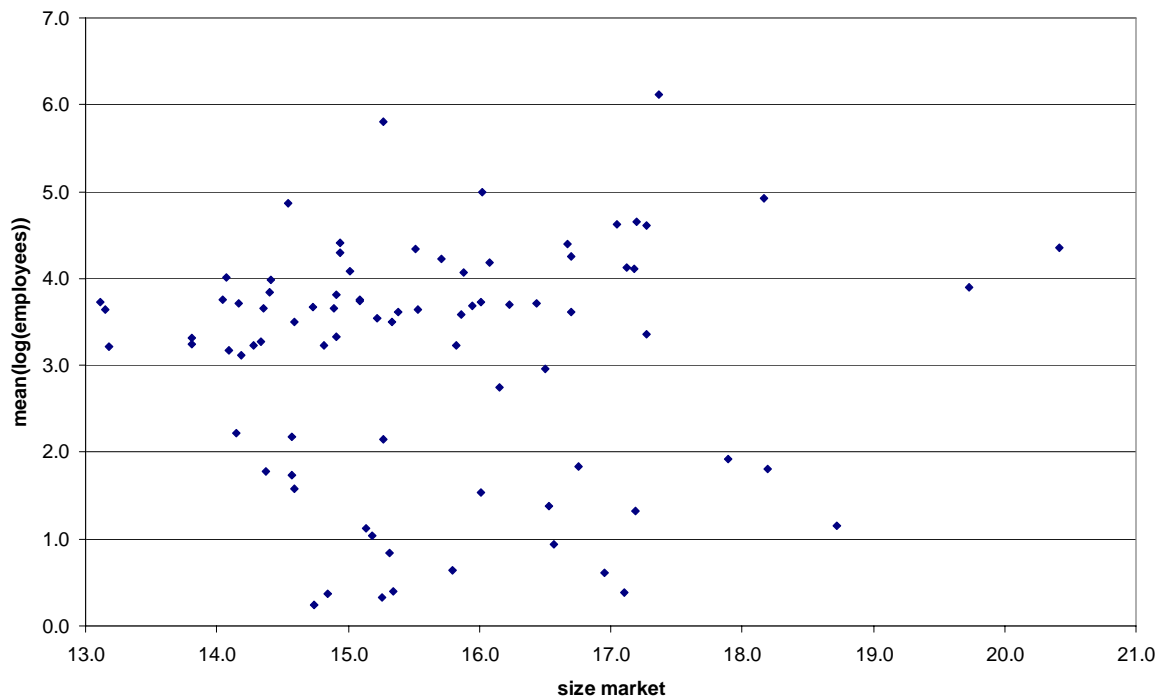Figure 4: Mean of Firm Size against Market Size
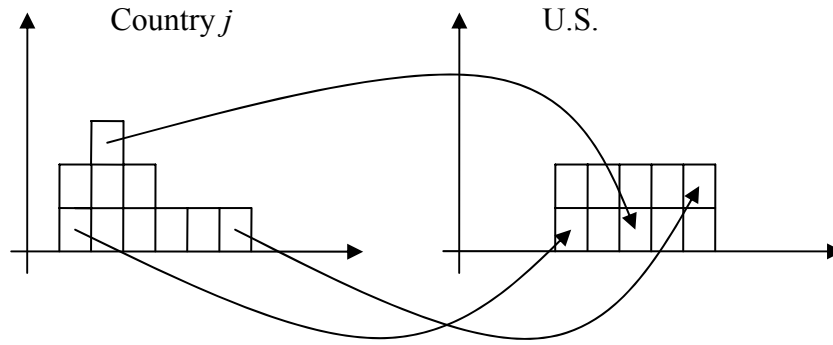
Figure 5: Histograms
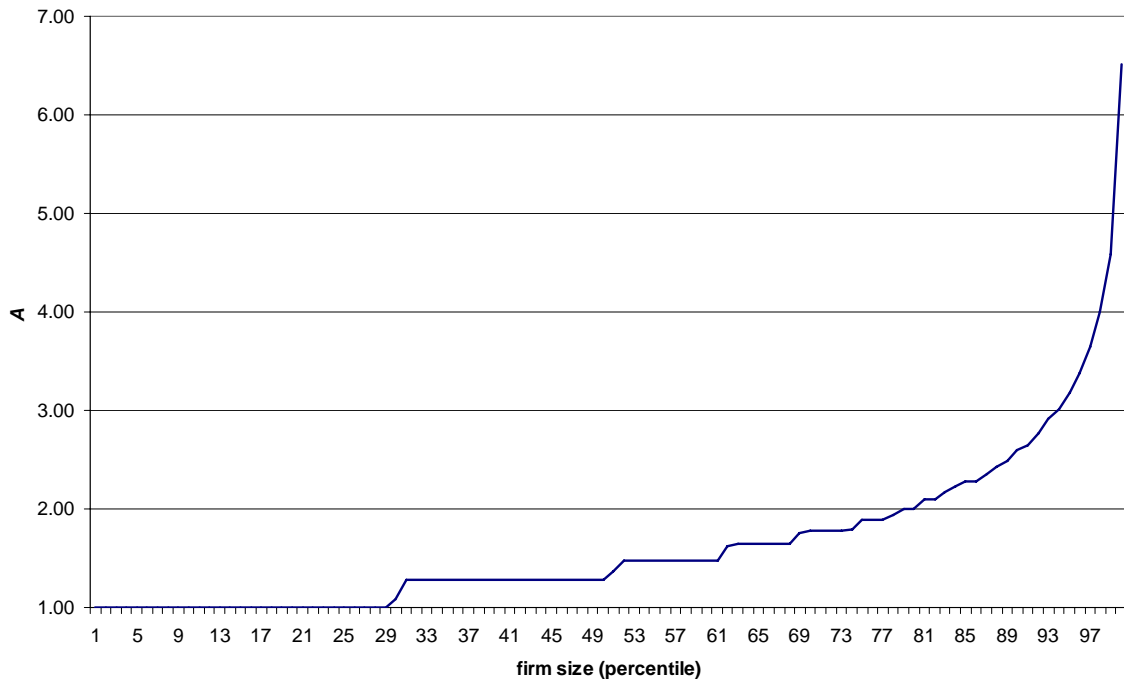

Figure 6: Firms' Productivities
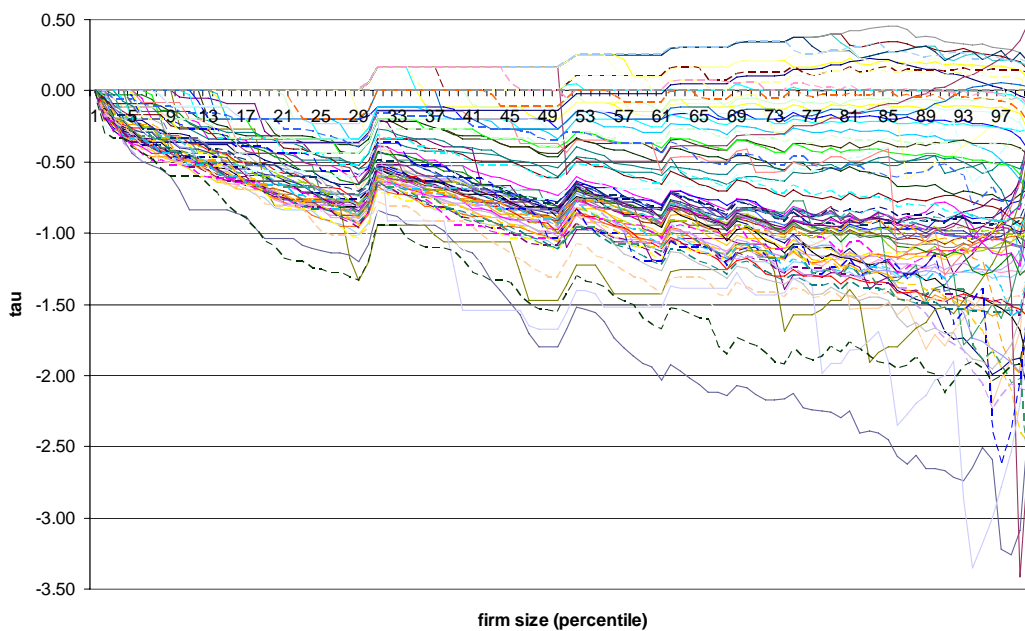
Figure 7: Tax Distortions for Various Countries

Figure 8: Misallocation Factor against Income per Worker