Cross Country Differences in Productivity: The Role of Allocative Efficiency

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Abstract

A growing body of empirical evidence suggests that, even in narrowly defined industries, there is significant heterogeneity in firm productivity and firm size. Moreover, consistent with core theoretical models of the size distribution of firms, the productivity and size distributions are closely related – that is, more productive firms are larger. However, the relationship between productivity and size varies across countries. A working conjecture is that this variation in the productivity/size relationship reflects differences in market distortions to allocative efficiency across countries. This is not a new hypothesis, but the burgeoning development of firm-level databases permits exploring it in richer and new ways. In this paper, we present empirical evidence of the within industry covariance between firm level productivity and market share using a widely-used decomposition proposed by Olley and Pakes (1996). We show that within the typical U.S. manufacturing industry, labor productivity is almost 50 percent higher than it would be if employment was allocated randomly. However, we also show that this empirical measure of the covariance between size and productivity is much lower on average in Western European countries and, in particular, in transition economies of Eastern Europe even if, in the latter, this covariance measure has increased significantly during their transition to a market-based system. While these findings are interesting and suggestive, there remain open questions as to the theoretical underpinnings behind these empirical measures that have been interpreted as measures of allocative efficiency. Thus, the paper also presents a theoretical model that provides a rationale for the existence of persistent differences in allocative efficiency. In the numerical analysis of this model, we evaluate the extent to which the Olley and Pakes decomposition is a useful summary measure of the impact of distortions to allocative efficiency.

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Introduction

There is a growing body of evidence suggesting significant heterogeneity in productivity levels across firms even in narrowly defined industries of most market economies (e.g. Bartelsman, Haltiwanger, and Scarpetta (2004), Syverson (2004), Foster, Haltiwanger and Syverson (2008)). This heterogeneity in firm-level performance is accompanied by substantial heterogeneity in the size of firms within narrowly defined industries. Consistent with core models of the size distribution of firms (e.g., Lucas (1978) and Melitz (2003)), the distributions of productivity and size are closely related – that is, more productive firms tend to be larger than less productive firms.[2] Given large differences in productivity across countries, a working hypothesis has emerged that distortions to allocative efficiency (i.e. more productive firms being larger) may account for differences in productivity across countries. This misallocation hypothesis is not new but the development of firm level databases in a variety of countries now permits exploring it more directly. In the literature, empirical decompositions of industry level productivity have been used as evidence in support of this hypothesis.[3] In this paper, we explore the theoretical underpinnings behind these decompositions and the misallocation hypothesis. In turn, we provide some evidence of the type and magnitude of distortions that could justify the observed cross-country differences in allocative efficiency.

[2] It is critical to emphasize that the moments we emphasize in this paper are within industry moments (of dispersion of size and productivity and the covariance/correlation between size and productivity). The models of the determination of the size distribution that we are exploiting are not the models needed to explain why, for example, the average steel factory is much larger than the average shoe factory. Moreover, comparisons of productivity measures across widely different industries requires addressing measurement and index number problems that have typically not been fully addressed in the firm level productivity literature. We note that even though the focus of the empirical and theoretical analysis is on within industry moments, variation in these within industry moments across countries can have important implications for cross country differences in outcomes. Essentially we are saying that distortions within industry are potentially relevant for cross country differences.

[3] There is a large related empirical literature that has investigated the extent to which reallocation is productivity enhancing. This literature also has issues associated with the validity of dynamic accounting decompositions (like those in Baily, Hulten and Campbell (1992) and Foster et. al. (2001)). A closely related but alternative approach to using empirical accounting decompositions has been to use a microeconometric approach. For example, there is a substantial microeconometric literature studying the determinants of market selection (e.g., Foster et. al. (2006) and Foster et. al. (2008) explore the determinants of market selection in terms of market fundamentals). The findings show that low productivity and low profitability establishments are much more likely to exit and that conditional on survival young establishments have faster productivity growth than incumbents. Findings such as these provide support for learning and selection models and in turn there has been investigation of whether learning and selection effects have been distorted in economies with market distortions (see, e.g., Eslava et. al. (2007)). A related approach has been to use a microeconometric approach with the firm-level data to explore factor adjustment dynamics in the presence of distortions to adjustment costs (see, e.g., Eslava et. al. (2008) and Petrin and Sivadasan (2006)). There are obvious advantages to microeconometric approaches (both structural and reduced form) but restricted access to firm level databases has yielded use of more summary approaches such as empirical decompositions. The latter are also attractive to practitioners and policymakers – the question of course as emphasized in this paper is whether such use is appropriate.

One of the most widely used empirical decomposition of the *level* of industry productivity is proposed by Olley and Pakes (hereafter OP, 1996): it decomposes industry-level productivity into an *un-weighted firm level average* and a *covariance term*, or cross term, reflecting the product between the deviation of firm-level productivity from the average industry productivity and the deviation in firm-level market shares from the average market share. The cross term is a summary measure of the *within industry* cross sectional covariance between size and productivity. It is this feature of the decomposition which is critical for our purposes since we explore the extent to which it is this margin that may vary across countries due to market distortions. As we show in this paper (and consistent with the burgeoning literature using firm level databases), this cross term is large and positive in advanced economies like the U.S. and much smaller in emerging and transition economies. In our analysis, we find that the OP cross term in U.S. manufacturing industries averages about 50 log points when decomposing industry-level labor productivity. This implies, in an accounting sense, that productivity in the average U.S. manufacturing industry is 50 percent higher than it would be if employment shares were randomly allocated. The OP cross term only reaches 20-30 log points in Western Europe and it was close to zero, if not negative, in Central and Eastern European countries at the beginning of their transition to a market economy. However, as the transformation process evolved in these economies, the cross term increased substantially.

The use of the OP cross term to explore the role of market distortions is, of course, not new. In their seminal contribution, Olley and Pakes found that the cross term (using a decomposition of industry TFP) increased substantially in the U.S. telecommunications equipment industry following the deregulation of the sector in the early 1980s. They argued that this was because the deregulation permitted outputs and inputs to be reallocated more readily from less productive to more productive firms. Following this logic, the increases in the cross term for emerging and transition economies following market-oriented reforms, could be interpreted as a quantitative measure of the success of these reforms, at least in terms of productivity.

In this paper, we explore the validity of these inferences regarding the OP empirical decomposition. Specifically, we exploit recent theoretical models that permit analyzing and quantifying the role of market distortions in the allocation of resources (in particular those by Banerjee and Duflo, 2003; Restuccia and Rogerson, 2007, and Hsieh and Klenow, 2007) and explore whether the common inferences about these empirical decompositions are valid. In like fashion, we assess whether the empirical decompositions provide useful information to calibrate and potentially fit models of misallocation. Our findings are largely supportive of the inferences in the literature regarding the Olley and Pakes decomposition. We find that increasing distortions to allocation for an economy in the manner suggested in the recent theoretical literature tends to decrease the OP cross term. However, we also find that distortions to market mechanisms can negatively affect alternative margins of resource allocation that, while related to a decrease in welfare, may not yield much change in the Olley and Pakes cross term. For one, distortions may impact not only the covariance for a given set of firms but also the selection process of market participants. The impact that market distortions can have on selection is nontrivial and has a variety of related implications. First, the impact of distortions on selection tends to change the average un-weighted productivity of market participants. Second, in a model where potential market participants must pay an entry cost before learning their productivity, distortions will affect the number of new firms that pay entry costs. Distortions can also affect the mix of firms and the scale of activity; for example the average firm size and the capital-labor ratio. All of these effects can have adverse impacts on aggregate consumption (or more generally welfare). These considerations imply that although measuring allocative efficiency in terms of the OP cross term provides useful information, it is certainly not exhaustive of the potential overall impact of distortions on market economies. As such, appropriate caution needs to be used in interpreting the patterns of empirical decompositions of productivity.

As noted above, our primary contribution to the literature is to bring together the recent theoretical models of misallocation with the large literature on empirical decompositions of productivity. However, we make some important innovations to the recent theoretical models that we think makes the model better fit the empirical evidence. We build our model from those recently developed by Restuccia and Rogerson (2007) and Hsieh and Klenow (2007). In these models, dispersion in labor productivity is driven by the presence of market distortions. That is, in both papers firms in a non-distorted economy hire workers up to the point when the marginal revenue product of labor is equal to the market-clearing wage. Moreover, the standard production functions used in the analysis have the property that the marginal product of labor is proportional to the average product of labor. The implication is that in these models, while there may be substantial dispersion in physical TFP, there should be no dispersion in labor productivity in the absence of distortions. However, in the data, a notable feature emphasized by Syverson (2004a) is that labor productivity dispersion within narrowly defined industries is very large even in countries with little or no distortions such as the U.S. Syverson (2004a) reports that, within narrowly defined industries, the difference in the U.S. between the 90^{th} and the 10^{th} percentiles of the firm-level productivity distributions is about 99 log points for total factor productivity (TFP) and about 140 log points for labor productivity. Understanding the nature of this productivity dispersion is critical in this context since it is this wide dispersion in productivity that provides considerable scope for misallocation. We augment our model by considering a number of additional factors that can justify the observed dispersion in productivity even in countries like the U.S. with arguably limited market distortions.

Another contribution of the paper is that we base our empirical analysis of allocative efficiency on a harmonized firm level database. As documented in Bartelsman *et. al.* (2008), this database overcomes many difficulties typically encountered in using cross country evidence from firm level databases given that the harmonized protocols for generating the firm level summary moments.

The paper proceeds as follows. Section 2 describes the harmonized firm level database. Section 3 presents some basic facts about productivity dispersion within the countries in our database as well as the empirical OP decompositions of productivity. Section 4 discusses briefly what we know about the nature of potential distortions to misallocation from the existing indicators of policy and institutional factors shaping the business environment in a number of industrialized and emerging economies. In Section 5, we develop the model of allocative efficiency with idiosyncratic distortions in the allocative process. Section 6 calibrates the model numerically to explore its implications in light of the empirical patterns in section 3. Section 7 uses reports the results from the numerical analysis of the calibrated model under different institutional settings. Section 8 presents concluding remarks.

2. The harmonized firm-level database and indicators of dispersion

To assess the degree of firm heterogeneity, the magnitude and characteristics of labor reallocation and, ultimately, their impact on sectoral and aggregate productivity, we use a harmonized firm-level database that covers 24 industrial and emerging economies.[4] These data have been collected from micro data from business registers, census and enterprise surveys playing particular attention at harmonizing, to the extent possible, of key concepts (e.g. entry, exit, or the definition of the unit of measurement) as well as at using common methods to compute the indicators. A detailed technical description of the dataset may be found in Bartelsman, Haltiwanger, and Scarpetta (2008)[5].

The database contains information on firm demographics, such as entry and exit, jobs flows, size distribution and firm survival, as well as on productivity distributions and correlates of productivity. In particular, information was collected on the distribution of labour and/or total factor productivity by industry and year, and on the decomposition of productivity growth into within-firm and reallocation components. Further, information is provided on the averages of firm-level variables by productivity quartile, industry, and year. The classification into about 40 sectors (roughly the 2-digit level detail of ISIC Rev3) coincides with the OECD Structural Analysis (STAN) database.[6]

For this paper, we highlight two dimensions of the firm-level datasets that are relevant to allocative efficiency. First, we look at the distribution of firm size across industries and countries. The observed wide and skewed distribution of firm size shows ample scope for improvements in allocative efficiency, if empirical observation also shows that the large (small) firms are not more (less) productive. Thus, an accompanying requirement for allocative efficiency effects to be important is for there to be dispersion in productivity across firms. The data allow looking at this second dimension of firm dispersion as well.

[4] The dataset includes 10 OECD countries: (Canada, Denmark, Germany, Finland, France, Italy, the Netherlands, Portugal, United Kingdom and United States) and 14 transition and emerging economies (Estonia, Hungary, Latvia, Romania, Slovenia; Argentina, Brazil, Chile, Colombia, Mexico, Venezuela, Indonesia, South Korea and Taiwan.(China)). However, different parts of the analysis use a smaller sub-set of countries due to data availability.

[5] The analysis of firm demographics is based on business registers, census, social security databases, or employment-based register containing information on both establishments and firms. Data for the analysis of productivity growth come more frequently from business surveys.

[6.] See www.oecd.org/data/stan.htm

- **Heterogeneity in firm size among incumbents:** Table 1 presents the ratio of the average size of the top to the bottom quartile of the distribution of firms by size in the total economy and the manufacturing sector. The table suggests a wide dispersion in firm size in all countries for which data are available. Moreover, in most countries the dispersion is larger in the manufacturing sector than in the total business sector and, within manufacturing in high-tech industries compared with sector average. It could be stressed, however, that the cross-country comparison of firm size dispersion may be influenced by the overall dimension of the internal market – especially for non-tradeables – and by the different sectoral composition of the economy. The data indeed suggest wider dispersion in firm size in some of the large economies – e.g. the United States – but also in some of the transition economies in Eastern Europe, where policy-induced distortions have allowed the survival of very large (formerly or still) state-owned firms together with many new smaller private units. In Annex Table 1, we present the indicators of firm size dispersion after controlling for industry composition. Within 2-3 digit manufacturing industries, the inter-quartile ratio of average firm size is considerable in all industries and countries.

- **Dispersion in labor productivity and TFP:** There are also wide differences in firms' productivity performance within manufacturing industries. Table 2 presents the difference between the top and bottom quartile of the log labor productivity. The differences are large: between 150-250 log points in most countries. Part of the significant cross-country differences is due to the difference sectoral composition (see column 2 in the Table), but even controlling for that, the gap in labor productivity between the most and the least productive firms is wide. And, as in the case of the dispersion in firm size, the high-tech sectors tend to be characterized by an even higher dispersion in all countries. To confirm this, Table 3 and Table 4 present the standard deviation in log labor and log multifactor productivity respectively for the different manufacturing industries. Moreover, there is a wider dispersion in labor productivity than in TFP for all the countries for which we have data (Figure 1).

Following the insights of Foster et. al. (2008) it is important to emphasize that the measures of TFP and labor productivity we are using in the empirical analysis from the harmonized data are revenue productivity measures. That is, it is based on real revenue using industry level price deflators per unit input. In what follows, we refer to revenue productivity measures for TFP as TFPR and revenue labor productivity measures as RLP. We refer to TFP based on physical productivity as TFPQ. Foster et. al. (2008) have shown for the selected products for which all these measures are available in the U.S. that these measures are closely related. Within narrowly defined products (7-digit product classes), the correlation between log(TFPQ) and log(TFPR) is 0.75 and the correlation between log(TFPQ) and log(RLP) is 0.56. Moreover, all exhibit substantial dispersion within narrow products with std(log(TFPQ)) = 0.26, std(log(TFPR))=0.22 and std(log(RLP))=0.65. Consistent with the core models on the relationship between size and productivity, the correlation between log(TFPQ) and log(output) is 0.28.[7] Moreover, consistent with product differentiation models being relevant even within narrowly defined product classes, the correlation between log(TFPQ) and log(price) (where the latter is the plant-level price) is -0.54.

These basic facts on these alternative measures of firm-level productivity help interpret our findings for other countries and serve as a benchmark for the model we develop. In terms of the latter, we want our benchmark model to reflect these basic relationships. The key relationships include: (i) substantial dispersion in TFPQ, TFPR and RLP; (ii) a positive relationship between TFPQ, TFPR and RLP; (iii) a positive covariance between size and productivity; and (iv) a negative relationship between TFPQ and plant-level prices consistent with the prediction that more productive plants have lower marginal costs and charge lower prices. In terms of interpreting our findings for other countries, the close relationship between TFPQ, TFPR and RLP suggests that patterns we find for, say, RLP, are likely to be relevant for the other measures as well. Still, we are careful in confronting our model with the empirical evidence to measure moments in the model in the same manner as we have in the data. With these findings in mind, we now turn to what we can learn from our harmonized data about the covariance between size and productivity within industries but across countries.

3. The Within Industry Size Productivity Relationship Across Countries

How are the size and productivity distributions within industries related to each other? How does the size productivity relationship vary across countries? To address this question, we look at a measure of allocative efficiency originally proposed by Olley and Pakes (1996). They note that in the cross section, the level of productivity for a sector at a point in time can be decomposed as follows:

$$\mathrm{Pr}\,od_t = \sum_i \omega_{it}\,\mathrm{Pr}\,od_{it} = \overline{\mathrm{Pr}\,od}_t + \sum_i (\omega_{it} - \overline{\omega}_t)(\mathrm{Pr}\,od_{it} - \overline{\mathrm{Pr}\,od}_t)$$

where $Prod_t$ is sectoral productivity, Prod_{it} is firm-level productivity, ω_{it} is the share of activity for the firm, and a 'bar' over a variable represents the unweighted industry average of the firm-level measure. The simple interpretation of this decomposition is that aggregate productivity is composed of two terms: the un-weighted average of firm-level productivity and a cross-term that reflects the extent to which firms with higher than average productivity have a greater market share. Olley and Pakes (1996) used this decomposition to show that following the deregulation of the telecommunications

[7] While this correlation is large and positive, it is far from one. Foster, Haltiwanger and Syverson (2008) note that this is because demand shocks play such an important role in the variation in size across establishments in the same industry. Our model below includes demand shocks although in this draft we have not fully explored the potential role of demand shocks.

markets in the U.S. in the early 1980s the cross term increased substantially in the telecommunications equipment industry.

This decomposition is easy to implement as it involves measures of the un-weighted average productivity and of the weighted average productivity. Measurement problems make comparisons of the levels of either of these measures across sectors or countries potentially problematic, but taking the difference between these two measures reflects a form of a difference-in-difference approach. As such, in principle the OP cross term is comparable across countries since a measurement problem that affects productivity levels is differenced out by the indicator.

In most of the analysis in this paper, we use log labor productivity at the micro level as our measure of P_{it}, and the firm's labor share in the industry as our measure of θ_{it}. We focus on labor productivity because it is more readily available (and likely more accurately measured) in our sample of countries. Foster, Haltiwanger and Krizan (2001) have shown that the patterns of the OP decomposition within a country are similar for labor productivity and total factor productivity. In the numerically simulated model discussed in the next sections, we consider labor productivity, but also TFP and consumption to derive inferences on the impact of distortions on the patterns of allocative efficiency. We also note that the measures of labor productivity we are using here are revenue-based measures of labor productivity. A small but important technical point to emphasize is that our implementation of the OP decomposition uses log productivity rather than levels at the firm. As such, we are decomposing the employment-weighted mean of firm-level log productivity. This makes our decomposition unit free which facilitates comparisons across industries and countries.[8]

Figure 2 shows the results of applying the OP decomposition at the industry level and then taking the weighted average results by industry for the countries in the harmonized database. We focus our attention on the cross term. We find that for virtually all countries the OP cross term is positive, suggesting a positive covariation between market share and its productivity at the micro level. For example, we find that the OP cross term is slightly less than 0.50 in the U.S. Since productivity is measured in logs, this implies that, within the average U.S. manufacturing industry, labor productivity would be about 50 logs point smaller if labor were allocated randomly across firms. The international comparison also suggests that the OP cross term is substantially higher in the U.S. than in most European countries. By contrast, there is evidence of high OP cross terms in some East Asian economies. Latin American economies have lower cross terms than the U.S., but higher than most European economies and the transition economies have the lowest cross terms.

While the OP cross term avoids the standard problems of cross country comparisons of productivity, it is not immune from measurement problems. In particular, measurement in the second moment of productivity or size within an industry that

[8] Our use of log productivity is a modification of the original implementation by Olley and Pakes (1996). They used TFP in levels for a single industry and examined the changes in the components of the decomposition over time which mitigates problems of units.

systematically varies by country because the firm level data is systematically noisier in one country than another will impact the OP cross term. For example, classical measurement error in the input size measure will reduce the OP cross term since it will mimic a more random allocation of market shares with respect to productivity. This consideration suggests some caution in assessing the observed cross-country patterns of the OP cross terms presented in Figure 1. To tackle this issue, we also present the evolution of the OP cross term over time within a country. To the extent measurement error within a country is relatively stable over time, the within country variation over time in the OP cross term will difference out the country-specific second moment measurement error.

The transition economies offer a rich context for assessing the potential links between distortions and allocative efficiency. Over the period observed by the available data (the 1990s), these countries undertook systemic reforms in their transitions from central-planning to a market economy. Arguably, many distortions affected the different margins of resource allocation, from barriers to entry, to distorted allocation of resources across firms, sectors and geographical areas. These distortions were gradually reduced if not eliminated in the transition to a market economy. Figure 3 shows the within country variation over time for the transition economies of the OP cross term. Interestingly, except for Estonia which starts with a relatively high cross term, the OP cross term increases in the transition economies and, in many cases, substantially. For example, in both Hungary and Slovenia, the OP cross term increases by about 20 log points during the transition.

Another advantage of examining the OP cross term over time within countries is that the variation can be put in the context of the overall patterns of productivity growth. Figure 4 shows the patterns of overall (industry-level) productivity, the un-weighted average productivity and the OP cross term for Hungary and Slovenia. Put in this context, the OP cross term has increased substantially but the overall and un-weighted productivity term have increased as well. Thus, while the differences in the OP cross-term are important, they do not account for most of the cross sectional or time series variation in productivity between and within countries.

The main points from Figures 2-4 are that the OP cross term is large, it varies substantially across countries and, within transition economies, it has increased substantially over time. These results are consistent with those found in other empirical studies for individual countries. First and foremost, Olley and Pakes, using TFP as the measure of productivity, found a positive and large cross term in the U.S. telecommunications industry. Moreover, they found that the cross term increased substantially following deregulation in the U.S. telecommunications industry. Along the same line, Eslava *et al.* (2004) found (also using TFP) that the OP cross term rose substantially within 3-digit Colombian industries in the 1990s – a period of substantial market reforms in Colombia. While the interpretation of the OP cross-term as capturing allocative efficiency is suggestive, in what follows we explore the relationship in the context of a model of heterogeneous firms faced with distortions.

4. Mapping different distortions to institutional and policy settings

What kind of market distortions can justify the observed differences in allocative efficiency and what type of reforms could bring about the improvements in efficiency as indicated in our OP cross terms? Over the past decade, a growing body of indicators have emerged covering a large number of countries and showing a marked variation in policy and institutional settings that could affect the process of resource allocation. These indicators generally point to considerable cross country variation in the degree of financial development, employment protection legislation, which affects the costs of adjusting the workforce to shocks, the costs of starting a new business as well as the cost associated with contract enforcement and bankruptcy procedures. As an example, Table 5 reports a sampling of such indicators for the countries covered in the empirical analysis discussed above. The reported cross-country differences in the indicators cannot be simply explained by differences between industrialized and developing and emerging economies. Indeed, while the degree of financial development tends to be higher in the industrialized countries in our sample compared with the transition economies and the Latin American countries, the rigidity of employment regulations as well as the costs of starting up a new business vary a lot also within the industrialized sub-sample of countries, and some of the latter countries are also characterized by high costs of enforcing a contract or closing down a business.

Bearing in mind the caveats discussed in the previous section about the cross-country comparability of the OP cross term, we note a statistically significant correlation between this term and both the indicators of financial development (positive) and employment rigidities (negative) and a weaker though correctly signed (negative) correlation between the OP cross term and the time to enforce a contract.

However, for the purpose of our analysis of allocative efficiency, we are also interested in policy-induced distortions that have an idiosyncratic impact on individual businesses. One way of obtaining an idiosyncratic impact is through differences in enforcement. In countries where enforcement is weak, it is easy to argue that the enforcement is also likely to have an arbitrary and capricious component. To shed some light on this issue, Figure 5 draws from the *World Bank Investment Climate Surveys* (see World Bank, 2004) and shows the differential impact of different institutional and policy factors on the operation and growth prospects of firms of different size. In particular, the figure reports the percentage point difference in the perceived constraint of a particular aspect of the business environment for medium-size (20-100 employees) and large firms (more than 100 employees) relative to micro firms (fewer than 20 employees). These estimates are obtained from firm-level probit regressions that, beyond size, also control for age, ownership, industry, country and export orientation effects.[9]

[9] The constructed dependent variables (one for each constraint) consist in binary variables equal to 1 if the firms report the constraint to be a major or very severe obstacle and 0 otherwise. A probit model is used to estimate the relationship between these dependent variables and a set of explanatory variables. The Figure reports the average size effect for two regions (European and Central Asia, ECA; and Latin America and the Caribbean, LAC). Aterido, Hallward-Driemeier, and Pages (2007) provide a more comprehensive analysis on how distortions affect firms with different characteristics differently exploiting within country variation using a difference-in-difference (DiD) approach to identify the impact of distortions on various measures of performance. Other papers have also used similar DiD approaches to assess how different

Figure 5 suggests significant differences in the way business environment conditions constrain the operation and growth prospect of small versus medium-size and large businesses. Medium-size and, especially, large businesses seem to be more affected by stringent labor regulations as well as by high taxes and cumbersome tax administration than small firms – most likely because it is more difficult for them to stay below the radar screen of the public authorities. Medium and large businesses tend to be relatively less affected by lack of access to, and the cost of, financing, as well as by political and economic instability and, not surprisingly, the anti-competitive effect of firms operating informally. There are also significant differences between the two regions – Latin America and the transition economies of Europe and Central Asia. In the latter, large firms tend to be the least affected by constraints in the business environment, with the exception to stringent labour market regulations that raise the labour adjustment costs. In Latin America – where informal activities loom large – large businesses are more affected than small and medium-size ones labor regulations as well as economic and policy uncertainties. All in all, this descriptive material provides evidence of how distortions in the institutional and policy setting characterizing the business environment can have very different impact on firms with different salient characteristics.

In the next section of the paper, we present a stylised model that allows us to rationalise the key empirical findings discussed above. In particular, we consider distortions that have an idiosyncratic component in the same manner as in Restuccia and Rogerson (2007) and Hsieh and Klenow (2007). While we interpret this recent empirical evidence as providing support for this core assumption and approach, much empirical work needs to be done to quantify the distributions of distortions faced by different firms and the extent to which distortions are correlated with firm characteristics including endogenous characteristics such as firm performance.

5. A Simple Model of Allocative Efficiency and Misallocation

To guide our analysis of distortions and allocative efficiency we develop a simple model drawing heavily from Restuccia and Rogerson (2007) and Hsieh and Klenow (2007). Key features of the model are diminishing returns and heterogeneous production units (as in Hopenhayn (1992) and Hopenhayn and Rogerson (1993)) that face *idiosyncratic* distortions (Restuccia and Rogerson (2007)). The model presented here differs from the recent literature on a number of key dimensions. As emphasized in the introduction, we want to be able to match the empirical observation that there is

distortions in the market affect firms with different characteristics. For example, in their pioneering work, of Rajan and Zingales (1998) exploits within country variation across industries to show that financially-dependent industries tend to have better growth performance in more financially developed countries. Moreover, Aghion, Fally, and Scarpetta (2007) using the same firm-level data of this paper found that financial development promotes not only the entry of small firms but also the post-entry expansion of the successful new businesses. Klapper, Laeven, and Rajan (2006) focus on micro data for a sample of European countries and show that financial development has a positive effect on gross firm entry in sectors that are more dependent on external financing while entry regulations tend to hamper entry of new firms. Finally, Micco and Pages (2006) and Haltiwanger, Scarpetta, and Schweiger (2008) find evidence that stringent labor regulations, by raising labor adjustment costs, discourage the entry of firms especially in sectors characterized by relatively high job turnover.

substantial dispersion in labor productivity within industries even in economies with little or no distortions such as the U.S. As such, we include two key features to account for such productivity dispersion even in the absence of distortions: quasi-fixed capital in the presence of transitory productivity shocks and overhead labor.

Starting with the behaviour of firms, we assume that firms produce according a production function given by:

(1) $Y_{it} = A_i \varepsilon_{it} (n_{it} - f)^{\gamma} k_{it}^{\alpha}, \gamma < 1$

where Y_{it} is output for firm in period *t*, A_i is the firm-specific, time-invariant productivity component for firm i, k_{it} is the amount of capital input of firm *i* at time *t*, n_{it} is the employment, *f* is overhead labor, and ε_{it} is an *iid* shock drawn from a time invariant distribution and observed each period after *k* is chosen and the decision to produce has been made. We also allow for decreasing returns to scale, possibly related to some unobserved fixed factor – such as managerial ability -- as in Lucas (1978). The decreasing returns hypothesis insures that the most productive firm/manager does not take over the market. The overhead labor implies that the distribution of labor productivity is not degenerate even in an economy without distortions (i.e., while the marginal revenue product of labor will be set equal to the wage rate, the average product of labor will vary with scale given overhead labor). Moreover, since capital is quasi-fixed, only labor will absorb the transitory shocks which will yield heterogeneity in the marginal revenue product of capital.

Firms face a downward demand schedule that arises from a differentiated products environment. The final good is assumed to be a CES aggregator of intermediate goods produced by the individual firms. The final goods sector is assumed to be perfectly competitive with the only inputs coming from intermediate goods. In particular:

$$Y_t = N_t^{(\rho-1)/\rho} (\sum_i \theta_i Y_{it}^{\rho})^{1/\rho}$$

where $\rho < 1$. The θ_i is a firm specific shifter in the aggregator that, from the perspective of the firm producing good *i*, acts as a demand shifter (firms will not know this upon entry). This implementation of the CES aggregator includes an adjustment factor to make the degree of substitution scale-free, as in Alessandria and Choi (2007) where N is the number of intermediate firms in operation.[10] This implies the inverse demand for good *i* is given by:

$$P_{it} = P_t \theta_i (\bar{Y}_t / Y_{it})^{1-\rho}$$

[10] As discussed by Alessandria and Choi (2007), including this adjustment factor permits distinguishing between the love of variety effect and the impact of market power.

where P_t is the aggregate price for the final good and $\bar{Y}_t$ is average output measured as final output divided by N.

Firms producing the intermediate goods maximize profits, within an environment with distortions to capital expenditures and nominal output, in each period given by:

$$(2) \quad \pi_{it} = (1-\tau_i)P_t\theta_i \bar{Y}_t^{1-\rho}[A_i\varepsilon_{it}(n_{it}-f)^\gamma k_{it}^\alpha]^\rho - w_t n_{it} - Rk_{it}(1+\kappa_i)$$

where τ_i is the firm specific and time invariant distortion to revenue for firm i, κ_i is the firm specific distortion to capital allocation, w_t is the wage paid to homogenous workers, and $R_t = r_t + \delta_t$, is the user cost of capital which equals the real interest rate plus the rate of depreciation. In considering these distortions, τ_i can be interpreted broadly to include any distortion that impacts the scale of a business, while κ_i represents any distortion that impacts the factor mix of a business. In what follows, we call these distortions a "scale distortion" and a "factor mix distortion" respectively. In addition, there is an extra cost of having employment deviate from some firm specific constant – we will specify the latter as the optimal employment in the absence of *iid* shocks and such additional costs.

To make the model and analysis tractable, we assume a simple ex ante and ex post timing of information and decisions in any given period. Ex ante, before a new firm enters, we assume that firms do not know their production, demand and distortion draws but they know the distribution of these idiosyncratic variables. There is a fixed cost of entry, given by c_e, that new firms must pay to enter and to learn their draws from the joint ex ante distribution of productivity and distortions, $G(A,\theta,\tau,\kappa)$. Once a firm learns their draws of A, θ, τ, and κ their values remain constant. Each period the firm is subject to a further idiosyncratic productivity shock that it learns after deciding whether to produce and choosing k each period.

Firms discount the future at rate $\beta = 1/1+r$ and face an exogenous probability of exiting in each period given by λ. Given free entry and the assumptions about the arrival of information, new firms enter up to the point where the expected discounted value of profits is just equal to the entry fee. Moreover, given that the draws are time invariant in the steady state, the present discounted value for an incumbent firm i ex post is given simply by:

$$(3) \quad W(A_i,\tau_i) = E_\varepsilon[\pi(A_i,\theta_i,\tau_i,\kappa_i)]/(1-\chi)$$

where

$$\chi = (1-\lambda)/(1+r)$$

In turn, the free entry condition is given by:

$$(4)\ W^{e} = \int_{A,\theta,\tau,\kappa} \max(0, W(A,\theta,\tau,\kappa) dG(A,\theta,\tau,\kappa) - c_{e}$$

New firms with a low productivity and/or a high scale (or factor mix) distortion draw will immediately exit upon learning their draws if they cannot cover their fixed operating costs. In what follows, we find that the fraction of firms that survive upon learning their productivity and distortion draws is an important factor for assessing the consequences of distortions. This is not surprising since distortions influence the pace of churning of firms and, in this model, this is captured by the pace of entry (the number of firms deciding to pay the entry fee) and exit (the number of firms that exit upon learning their draws).

The optimal capital and labor choices will depend on input prices and the idiosyncratic capital distortion. In addition, the optimal labor choice will depend upon the realization of the iid shock. It is useful to start backwards within a period considering optimal employment for a given capital stock which must satisfy:

$$(5)\qquad \gamma\rho(1-\tau_{i})(\theta_{i} P_{t} \bar{Y}_{t}^{1-\rho} [A_{i}\varepsilon_{it} k_{it}^{\alpha}]^{\rho} (n_{it} - f)^{\gamma\rho-1} = w_{t}$$

In turn the optimal capital stock must satisfy:

$$(6)\ k_{it} = [(1-\tau_{i})\alpha A_{i}^{\rho} P_{t} \theta E_{\varepsilon} (\bar{Y}_{t}^{1-\rho} (\varepsilon_{it}(n_{it} - f)^{\gamma})^{\rho})) / (R(1+\kappa_{i})]^{1/(1-\alpha\rho)}$$

Output and profits for the operating firm are given by (1) and (2). Even though the firm is subject to an *iid* shock each period, the expected profits of the firm are the same every period and the optimal capital stock is the same every period. The firm adjusts to the ex post information each period about productivity by adjusting employment. Even in the absence of distortions, there will be dispersion in labor productivity given the overhead labor interacting with the heterogeneity in TFP and the heterogeneity in capital stocks.

To close the model we must describe labor supply and the behaviour of households and workers. In this case, this is relatively straightforward as a fixed number of households are assumed to supply labor inelastically so that aggregate labor supply is equal to N^{s}. Aggregate labor demand is given by the sum of labor demands for operating firms from (5). In equilibrium the number of firms and wages must satisfy both the free entry condition and that labor demand equals aggregate labor supply.

$$W^{e} = 0, N_{t}^{d} = N_{t}^{s}$$

Aggregate consumption plus resources spent on entry and depreciation will equal aggregate output in the stochastic steady state:[11]

$$C_t + E_t c_e + \delta K_t = Y_t$$

Where K_t is the aggregate of capital of ex-post operating firms.

Underlying this model is the standard assumption that households maximize utility and given the assumption of inelastic labor supply this is assumed to be given by for the representative household:

$$\sum_{t=0}^{\infty} \beta^t U(C_t)$$

Subject to the budget constraint:

$$\sum_{t=0}^{\infty} p_t(C_t + K_{t+1} - (1-\delta)K_t) = \sum_{t=0}^{\infty} p_t(w_t N_t + r_t K_t + \pi_t)$$

Where p_t is the time zero price of period t consumption, w_t and r_t are the period *t* rental prices of labor and capital measured relative to period t output, and π_t is the total profit from the operations of all plants. A standard result emerges from the first order conditions of this problem given by:

$$r_t = R_t - \delta \ = (1/\beta) - 1$$

So the real interest rate and rental cost of capital is pinned down by the discount factor for utility and the capital depreciation rate.[12]

6. Calibration of Model

We calibrate the model in two steps. First, we choose some "benchmark" parameters for the model and explore its numerical properties for a non-distorted economy. The parameters are chosen to match key features from the U.S. data. We then explore the implications of measures of allocative efficiency for a non-distorted economy. This analysis helps us to understand the interactions in the model and the relationship between firm size and productivity and the resulting measures of allocative efficiency look like when there are no idiosyncratic distortions. Second, we consider alternative forms of institutional distortions. The goal here is to understand the impact of these distortions on the moments from the micro data as discussed in Section 3. In particular, we are interested in understanding the extent to which the OP empirical

[11] In steady state gross investment is only equal to replacement investment.

[12] See Restuccia and Rogerson (2007) for further discussion.

decomposition is a valuable metric for assessing the extent of distortions to an economy. We also explore the extent to which other metrics are useful summary measures for the extent of distortions.

In exploring the model simulations it is useful to note that there are a number of possible measures of firm-level productivity that are interesting to examine in this context. The measure of physical TFP (what Foster et. al. (2008) and Hsieh and Klenow (2007) call TFPQ)) is given in the model by the product $A\varepsilon$ with the permanent component of physical productivity given by A. The measure of revenue TFP (what Foster et. al. (2008) and Hsieh and Klenow (2007) call TFPR) and the associated measure of revenue labor productivity (what we refer to as RLP) are also of interest. As shown in Appendix A, the employment weighted average of revenue labor productivity yields the total final output divided by total employment. This reflects the point that firm-level prices are relevant values for aggregating the intermediate goods into final output. In what follows, we examine all of these different measures of firm-level productivity within the context of the model simulation. It is important to note that in all of the numerical analysis, the moments and decompositions we report are based on log(TFPQ), log(TFPR) and log(revenue labor productivity) or log(RLP). In the discussion that follows in the text, when we refer to TFPQ, TFPR and labor productivity we typically omit the reference to logs for expositional convenience but in all cases log based measures are used.

We also note that in our numerical analysis of the theoretical model we consider an OP decomposition of revenue labor productivity that corresponds to what we measure in the data. That is, one of the OP decompositions we consider is based on the employment-share weighted average of firm-level log revenue labor productivity. The point of this is to investigate how the moments associated with this specific decomposition vary as the institutional settings (in terms of market distortions) varies. In the numerical analysis we also consider OP decompositions of TFPR as part of our exploration of the relationship between alternative moments of firm-level productivity measures and distortions.

For our calibration of the non-distorted economy, we select a number of the parameters to be in the range from existing evidence. These include:

- $\gamma = 0.95$, (returns to scale)
- $\alpha = 0.3$, (capital output elasticity)
- $\lambda = .10$, this is consistent with evidence of exit rates in the United States and other OECD countries for businesses more than five years old (Bartelsman, Haltiwanger, and Scarpetta (2008) and Davis, Haltiwanger and Jarmin (2008))
- R=.02, and $\delta = .10$, consistent with long run real interest rates in OECD countries and typical depreciation rates from national accounts.
- $\rho = .8$, this is in the Broda and Weinstein (2006) range and imply a markup of 25 percent.

For parameters where there is less guidance from existing evidence, we choose parameter values with the objective of matching the U.S. moments regarding the labor productivity and OP decomposition in Section 3. These parameters include overhead labor, the entry cost, and the dispersion of the productivity shocks (e.g., A, ε, θ). We report the values of these parameters in the discussion of the results of the calibration below and discuss their reasonableness relative to the evidence in the literature.

7. Results from Calibrated Model

The results for the calibration for the non-distorted economy are reported in first column of each of the panels of Table 6. Unlike Restuccia and Rogerson (2007) and Hsieh and Klenow (2007), our model yields dispersion in TFPR and labor productivity in the non-distorted economy given the presence of overhead labor, transitory shocks and quasi-fixed capital. Even though there is positive dispersion in RLP and TFPR in the non-distorted economy, the calibrated dispersion for the non-distorted economy is substantially lower that the range reported in Tables 3 and 4 for the U.S. for RLP and TFPR, respectively. Moreover, the calibrated dispersion for TFPQ is much higher in the non-distorted economy than that for labor productivity or TFPR. In this respect, we do not capture the patterns discussed in section 2 that suggest that measured dispersion in labor productivity is much higher than dispersion in either TFPR or TFPQ.

These patterns in the calibrated results reflect the fact that there still is some tendency for marginal revenue products to be equalized. Firms with high physical productivity in this model are larger in size and produce more. As such, they charge lower prices and along with the decreasing returns this lowers marginal revenue products. Given the frictions (overhead labor, transitory shocks and quasi-fixed capital), labor productivity and TFPR exhibit dispersion and are highly correlated with physical productivity and the level of activity of the firm. The correlation between TFPQ and TFPR is 0.97, the correlation between TFPQ and labor productivity is 0.90, the correlation between employment and labor productivity is 0.51. Moreover, as reported in Table 6, the correlations between measures of size and productivity for RLP, TFPR, and TFPQ are all very high. The relationship between labor productivity and employment from the non-distorted economy is depicted in Figure 6. The strong positive relationship is clearly evident. The observed patterns reflect all of the factors discussed above as well as the discrete distributions used in the simulations.

The strong positive correlations between labor productivity and employment and TFPR and output yield positive and large OP cross terms. The OP cross term for labor productivity (which uses employment weights) is 0.21, the OP cross term for TFPR (which uses revenue weights) is 0.25, and the OP cross term for TFPQ (which uses output weights) is 0.73. While these are substantial OP cross terms in an absolute sense the value for the OP cross term involving labor productivity is still only about half the value reported for the U.S. in Figure 2.

In the existing framework, it is difficult to change the pattern of labor productivity and TFPR dispersion having smaller dispersion than TFPQ. As noted there is still a tendency for equalization of marginal revenue products which in this setting implies reduced dispersion of TFPR and labor productivity. Further frictions could be added to the model (e.g., making the model explicitly dynamic with adjustment costs) but this will not by itself reverse the finding of higher TFPQ dispersion than labor productivity dispersion (but can potentially reduce the gap between TFPQ dispersion and labor productivity dispersion). For the latter, it is likely that a richer model of wage determination is required where wages are not determined in a competitive labor market.[13] That is, if firms face different wages then this can potentially serve a source of variation in labor productivity across firms. For now, we leave the investigation of these issues for future work but note that our model is only partially successful in capturing U.S. moments on dispersion and the OP cross term in labor productivity. We view that the frictions we have incorporated in the model as first steps towards capturing the full range of frictions that are apparently necessary to match empirical observations on labor productivity dispersion.

Other factors also work against having a high labor productivity dispersion and a OP cross term for labor productivity in this setting. For example, while including overhead labor is important in this context, increasing the value of f also yields less survival of entering firms. That is, firms with low productivity draws are more likely to exit. This theme that it is important to take into account market selection effects plays a role in the impact of distortions below.

Beyond the moments on productivity dispersion and the OP cross terms, we also report a number of additional statistics from the numerical simulation which provide both perspective on the reasonableness of the benchmark simulation and parameters and are quite useful in terms of providing insights about the alternative margins that distortions may impact. The capital cost share of total output (defined as RK/Y) in the non-distorted economy is 0.22. The overhead share of labor defined as the total overhead labor divided by total employment is equal to 0.12 in the non-distorted economy. In manufacturing in the U.S., non-production workers account for roughly 0.30 of all employment. Classifying all non-production workers as overhead labor is probably too strong an assumption but this suggests our fraction is not unreasonably high. The fraction of firms that after entering and learning their productivity and distortion draws decide to continue is 0.47 in the non-distorted economy. This is roughly consistent with the fifty percent exit rate of new firms in their first five years in the U.S. economy (see, Haltiwanger, Jarmin and Miranda (2008)).

We now turn to the implications of the model with distortions. For distortions, we consider three different cases:

(i) A random ex-ante scale distortion case with the ex-ante mean(τ)=0 and corr(A, τ)=0

[13] We thank John Fernald for pointing out that differences in factor elasticities across plants might also be relevant. We note that the dispersion in RLP is twice that of TFPQ so this would require substantial within industry variation in factor elasticities.

(ii) A random ex-ante factor mix distortion case with the ex-ante mean(κ)=0 and corr(A, κ)=0

(iii) A correlated ex-ante scale distortion case ex-ante mean(τ)=0 and corr(A, τ)>0.

Columns 2 and 3 of Table 6 show the results using uncorrelated scale distortions but with different levels of dispersion of the distortions. The reported institutional parameter statistics are from the ex ante distribution. It is important to note that the ex post distributions have different properties. That, even with zero ex ante mean and zero ex ante correlations, we obtain via selection an ex post distribution of distortions that is non random, non zero mean. This makes sense as firms with low τ draws are more likely to survive and those with high τ draws are less likely to survive. Given this pattern, the average surviving firm actually faces a negative distortion (the equivalent to a positive subsidy) and the ex-post correlation between distortions and productivity is positive (this is because one needs to be high productivity to survive with a high distortion).[14]

The impact of the distortions in the uncorrelated scale case (using the results from column 3 of Table 6) is visually evident in Figure 7 showing a number of high productivity very small firms that have been adversely made smaller by the distortions and fewer high productivity large firms than in the non-distorted economy in Figure 6. A firm will be large here only if they obtain both a high productivity draw and a low distortion draw. As a consequence, we observe lower OP cross terms for labor productivity and TFPQ and a slightly higher OP cross term for TFPR. We see that all correlations between size and productivity decline especially for column 3. However, a number of other margins are also impacted. We see much lower survival which implies too much churning and paying of entry costs relative to the non-distorted economy as well as too little production. We also see that the capital cost share of output is much higher than in the non-distorted economy. We don't see much change in the unweighted means of TFPQ or TFPR but we actually see an increase in the mean of labor productivity. This reflects the higher capital share and the too low survival rate. We observe higher dispersion in TFPR, slightly higher dispersion in TFPQ but no change in dispersion in labor productivity. We find that consumption per capita is much lower (as much as 41 log points lower than the non distorted economy in column 3) given the distortions. We don't find much change in aggregate labor productivity (measured by aggregate final output per worker). Interestingly, we find that as we increase the dispersion of the distortions these effects are magnified – lower consumption, higher dispersion, and lower size-productivity relationships either measured by the correlations or by the OP cross terms.

[14] One open issue both conceptually and empirically is that we permit distortions to be both positive and negative. A business with a negative distortion effectively has a subsidy for activity on some margin. A related issue is that we, as in Hsieh and Klenow (2007) view these distortions as distortions not taxes while in the Restuccia and Rogerson (2007) model these distortions as taxes. The latter is relevant for the welfare/consumption impact as Restuccia and Rogerson make a lump sum transfer that could be positive or negative depending on the tax revenue.

Columns 4 and 5 of Table 6 show the patterns for correlated scale distortions. The relationship between labor productivity and employment for the correlated scale distortion case (for column 5) is depicted in Figure 9. Here the evidence of the distortions is very evident with much less of a systematic relationship between labor productivity and employment. The correlation between labor productivity and employment for column 5 drops to 0.38 and the other correlations between size and productivity drop substantially as well. The OP cross term for labor, TFPR and TFPQ decrease to 0.03, 0.17 and 0.45 respectively. Even though the size-productivity relationships clearly reflect the impact of distortions in this case, other margins are also distorted. For example, the capital cost share is also distorted. The reduction in consumption per capita is substantial in column 5 with a reduction of 51 log points relative to the non-distorted economy. We also observe a large decline in aggregate labor productivity (39 log points).

Column 4 depicts similar patterns but somewhat muted given the smaller dispersion and correlation of distortions. In column 4, consumption declines by 26 log points and aggregate labor productivity by 28 log points. The size-productivity correlations and OP cross terms are substantially smaller than the non-distorted economy but larger than the highly distorted case depicted in column 5.

It is instructive to note that, in comparing the OP cross term for the correlated scale case of 0.03 of column 5 to the OP cross term for the non-distorted economy of 0.21, there is roughly a 20 log point swing. This 20 log point swing is comparable to the variation within countries in the OP cross term measure from actual data in Figure 3 for the transition economies suggesting this class of models has the potential to account for a substantial fraction of the magnitude of variation observed in the data. However, as noted above there are a number of features of the productivity distributions and OP decomposition patterns that are not yet well captured by this model.

The patterns for the uncorrelated factor mix distortion are reported in the rightmost column of Table 6. The relationship between labor productivity and employment for the uncorrelated factor mix distortion case is depicted in Figure 9. Interestingly, while careful examination shows the pattern is distorted relative to Figure 6, the qualitative nature of the relationship is similar to the non-distorted economy. Consistent with this pattern, we find only a modest decline in the OP cross term for labor productivity. We find no decline in the OP cross term for TFPQ and a slight increase in the OP cross term (relative to the non-distorted economy) for TFPR. In like fashion, there is not much change in the size-productivity correlations relative to the non-distorted economy. However, we find substantial effects on a number of other margins including the capital cost share of output and the fraction of entrants that survive. As with the scale distortion case, those firms that draw especially high distortions exit. The consequences of these distortions in terms of consumption are non-trivial with a reduction of about 21 log points even though we observe relatively modest effects on the moments involving productivity including the OP cross term. In this case, we observe an increase in aggregate labor productivity reflecting the higher capital share.

What lessons do we draw from these calibrations? First, consistent with the intuition from Olley and Pakes (1996) and further interpretations in the literature, we find that economies with distortions to the allocation of activity in terms of scale distortions have distorted size-productivity relationships as measured either by the OP cross terms or the size-productivity relationships. As an important aside, we have found that the impact on the OP cross terms closely mimics the impact on the size-productivity correlations. In this respect, these moments essentially capture the same variation. Second, we find the size-productivity relationship is distorted exactly in those cases where distortions lower aggregate labor productivity. In cases where aggregate labor productivity does not decline substantially, we find this margin (the size-productivity relationship) is also not much impacted. Third, we find that many other margins may be adversely impacted other than the size-productivity relationship including the market selection margin as well as the mix of capital and labor in an economy. As these other margins are impacted, the consequences for consumption are sometimes large even when the size-productivity margin is not impacted. It is clear in this respect that the size-productivity relationship is not a sufficient statistic to capture the nature and impact of distortions. Put differently, the size-productivity relationship is an important margin but not the only margin.

A related question is whether there are other summary statistics from the productivity distribution that could be used as summary statistics about the performance of an economy. One candidate summary statistic suggested by Hsieh and Klenow (2007) is to use the dispersion of TFPR as a metric to identify distortions. In their model, TFPR (and labor productivity) only exhibits dispersion because of distortions.[15] Also, for the distortion cases they consider, TFPR dispersion increases with distortions. In our model, there is substantial dispersion in TFPR even in the non-distorted economy. However, consistent with their findings and intuition, we see some evidence that increasing distortions increases dispersion in TFPR in our model. For example, in comparing columns 1-3 of Table 6, dispersion in TFPR is higher with distortions than without and increases in the dispersion of distortions. However, in considering the role of correlated distortions observe that the dispersion in TFPR in column 5 is the same as in column 3. However, in column 5 both the dispersion of distortions as well as the correlation of distortions with productivity is much higher. In addition, column 5 has much lower aggregate consumption than column 3. Thus, TFPR dispersion is also not a sufficient statistic in our model to identify the nature and impact of distortions. The suggested inference is that there are multiple moments (and multiple margins) that are impacted by allocative distortions. A challenge for future work is to pin down theoretically and empirically the most relevant moments. We would argue that we have identified one relevant moment and certainly think that dispersion is another candidate moment. However, even in our simple model there are many other margins potentially adversely impacted so additional moments (and margins) need to examined.

[15] In unreported results we have verified that our model yields no dispersion in TFPR or labor productivity if we set overhead labor equal to zero and we remove transitory productivity shocks.

8. Concluding Remarks

In this paper, we provide empirical evidence of substantial within industry dispersion in measured labor productivity and measured TFP as well as in firm size across a wide range of countries. We also show that the distributions of productivity and size are closely related to each other but also that their relationship varies significantly across countries. Using the Olley and Pakes (1996) decomposition, we provide a summary measure of the extent to which size and productivity exhibit positive covariance within industries. The evidence presented suggests that the size/productivity relationship is stronger in the more advanced economies and becomes stronger for transition economies as they move through the transition to a market economy. Moreover, there are variations in the size/productivity relationship among the market economies that is suggestive of differences in market distortions to allocative efficiency.

It is tempting to conclude from the empirical evidence alone that the OP decomposition is a useful summary measure for evaluating the efficiency in the allocation of resources of different countries. While it is tempting to draw this inference, the OP decomposition is an accounting decomposition. As such, it is an open question in what classes of theoretical models (if any) where allocative efficiency plays a potentially important role does the OP decomposition yield such inferences. In this paper, we exploit some recent theoretical models developed in the literature that are well suited to take a first step towards answering this question. The models (developed by Banerjee and Duflo (2003), Restuccia and Rogerson (2007) and Hsieh and Klenow (2007)) all suggest that the level of productivity in a country depends critically on the nature and extent of idiosyncratic distortions to the incentives of firms to produce and to hire factors of production. We modify these models in important ways to capture features of the empirical evidence that are missing from these models. In particular, we consider quasi-fixed capital in the presence of transitory and permanent productivity shocks and overhead labor. These frictions enable our version of the model to yield substantial dispersion in labor productivity within narrowly defined sectors even in economies that arguably (e.g., the U.S.) have relatively modest distortions.

Our model simulations suggest that the size/productivity relationship within an industry as captured by the OP cross term is a potentially important margin impacted by distortions to allocative efficiency. That is, we find we find that adding distortions to our model tends to yield reductions in the OP cross term and equivalently in the size-productivity correlation within industries. However, we also find that even in our reasonably simple setting many other margins are potentially impacted by distortions including the market selection margin and the factor mix margin. Distortions to either of these latter margins is associated with reductions in consumption without necessarily yielding changes in the OP cross term (or almost equivalently in the size/productivity correlation).

Note however that we find the OP cross term is most adversely impacted by distortions in the case when the distortions lower aggregate labor productivity. This suggests that in countries exhibiting low levels of aggregate labor productivity that a potentially important margin that may be contributing to this low aggregate labor productivity is a low covariance between labor productivity and employment. Put simply, if more productive firms are not larger in a country this is likely an indication that there is a distortion to this core prediction of market based models of the size distribution of activity.

Our analysis should be viewed as a first step in many ways. While we believe these recent models of misallocation with idiosyncratic distortions offer rich new insights they are quite simple relative to the theoretical and empirical models on firm behavior in the literature. These misallocation models are steady state models with no meaningful dynamics. A large literature exists that models and empirically analyzes firm dynamics including the role of selection and learning effects for young firms as well as the adjustment dynamics of capital and labor. The type of distortions we include in our model quite plausibly distort these dynamics – indeed there are many models in the literature that make just this point. In a related way, there are a number of dynamic empirical decompositions of productivity that have been used in an analogous fashion to the OP decomposition. It would be of interest to evaluate the validity of these dynamic decompositions within the context of appropriate models of firm dynamics with distortions to the reallocation process. We think that adding dynamics to these models is of interest for many reasons including providing sources of frictions beyond those that we use here to capture the observed dispersion in labor productivity.

As a final note of caution and perspective, the empirical approach taken here has been to focus on firm-level labor productivity even though it clear for many reasons (including the results from the model presented here) that it would be preferable to have moments capturing firm level TFPQ and TFPR. There are a number of countries (e.g., the U.S., many Western European, some transition and some emerging) where it is feasible to construct measures of firm level TFPR for manufacturing firms and a very small number of countries where it is feasible to disentangle TFPR into its price and TFPQ components for manufacturing firms. However, for many countries and for most non-manufacturing firms, the most readily available measure of productivity at the firm level is revenue labor productivity. Interestingly and fortunately in some respects for analysis, in the countries where it is feasible to measure all of these alternatives, the correlations between TFPQ, TFPR and labor productivity are high at the firm level. Moreover, basic moments exhibit similar properties suggesting that the type of analysis presented here yields insights even when limited to measures of labor productivity. Still, an obvious additional direction for research and analysis of the type presented here is to use moments of TFPQ and TFPR as available.

Appendix A Revenue Firm-Level Productivity and Aggregate Labor Productivity

In this appendix, we explore the relationship between firm-level revenue labor productivity and a measure of aggregate labor productivity based upon final output. Revenue labor productivity for an individual producer is given by :

$$RLP_{it} = P_{it} Y_{it} / n_{it}$$

Consider that the firm level price in the model is given by:

$$P_{it} = P_t \theta_i (\bar{Y}_t / Y_{it})^{1-\rho}$$

so that revenue productivity at the micro level can be written as (without loss of generality after normalizing aggregate industry price to one):

$$RLP_{it} = \theta_i (\overline{Y}_t)^{1-\rho} Y_{it}^{\rho} / n_{it}$$

This implies that the employment-weighted average of revenue productivity is given by:

$$\sum_i (\theta_i (\overline{Y}_t)^{1-\rho} Y_{it}^{\rho}) / n_t = (\overline{Y}_t)^{1-\rho} \sum_i (\theta_i Y_{it}^{\rho}) / n_t$$

where note that lower case n is the number of workers (not the number of firms N).

But note that expression embedded here given by:

$$(\overline{Y}_t)^{1-\rho} \sum_i (\theta_i Y_{it}^{\rho}) = (\overline{Y}_t)^{1-\rho} (\sum_i (\theta_i Y_{it}^{\rho}) / N_t) N_t = ((\sum_i (\theta_i Y_{it}^{\rho}) / N_t)^{1/\rho})^{1-\rho} (\sum_i (\theta_i Y_{it}^{\rho}) / N_t) N_t = \overline{Y}_t N_t = Y_t$$

so that our weighted average of revenue productivity is exactly equal to aggregate labor productivity defined as total (final) industry output divided by total employment.

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Table 1.

Distribution of firms by size
(ratio of the mean size of fourth to the first quartile of the distribution of firms)

Country	Total economy	Total manufacturing	High & medium tech industries
Finland	15	37	46
France		52	77
Italy	32	66	111
Netherlands	32	113	192
Portugal	34	60	78
United Kingdom		133	221
United States	76	236	381
Argentina	29	47	52
Brazil	65	74	117
Estonia	35	56	85
Latvia	51	47	44
Mexico	51	108	277
Romania	114	433	
Slovenia	126	283	314
Chile[1]		16	15
Colombia[1]		25	24
Venezuela[2]		39	29

Table 2

Labor Productivity dispersion, manufacturing, 1990s
(differences between the fourth and the first quartile, log of mean levels for quartile)

	Total manufacturing		
	weighted average[2]	controlling for industry comp.[3]	High & medium tech industries[1]
DEU	2.48	1.47	
EST	2.47	2.29	2.59
FIN	1.64	1.33	1.51
FRA	1.53	1.18	1.32
GBR	1.38	1.14	1.43
LAT	2.66	2.51	2.71
NLD	1.46	1.16	1.24
SLO	2.20	1.90	5.15
USA	1.59	1.39	1.81

1. Chemicals, Electrical and optical equipment, Motor vehicles, aircraft and railroad equipment
2. Weighted averages of industry-level data.
3. Country fixed effects in inter-quartile regression with country, industry and year fixed effects.

Table 3.

STANDARD DEVIATION OF LOG LABOR PRODUCTIVITY

	DEU	FIN	FRA	NLD	PRT	UK	USA
Total manufacturing (weighted avg)	**0.75**	**0.66**	**0.55**	**0.53**	**0.80**	**0.54**	**0.57**
Food products, beverages and tobacco	0.95	0.83	0.75	0.78	0.92	0.73	0.74
Textiles, textile products, leather and footwear	0.75	0.60	0.69	0.60	0.82	0.56	0.75
Wood and products of wood and cork	0.72	0.63	0.50	0.36	0.82	0.53	0.57
Pulp paper, paper products, printing and publishing	0.85	0.71	0.52	0.45	0.71	0.52	0.53
Coke refined petroleum products and nuclear fuel		1.10	0.54	0.96	1.02		0.95
Pharmaceuticals		0.68	0.57	0.54	0.86	0.50	0.62
Chemicals excluding pharmaceuticals		0.78	0.55	0.54	1.01	0.60	0.62
Rubber and plastics products	0.44	0.50	0.47	0.44	0.72	0.48	0.50
Other non-metallic mineral products	0.57	0.67	0.55	0.51	0.76	0.65	0.58
Basic metals		0.79		0.58	0.80	0.66	0.65
Fabricated metal products except machinery and equipment		0.47		0.43	0.68	0.45	0.50
Machinery and equipment n.e.c.		0.57	0.44	0.41	0.72	0.45	0.47
Office accounting and computing		0.90		0.48	0.87	0.61	0.72
Electrical machinery and apparatus nec		0.56	0.46	0.47	0.79	0.45	0.53
Radio, television and communication equipment		0.92	0.54	0.46	0.89	0.55	0.65
Medical precision and optical instruments		0.39	0.49	0.49	0.71	0.45	0.49
Motor vehicles, trailers and semi-trailers		0.37	0.46	0.41	0.74	0.46	0.52
Building and repairing of ships and boats		0.54		0.53	0.75	0.41	0.46
Railroad equipment and transport		0.40		0.47	0.62	0.52	0.48
Aircraft and spacecraft		0.38			0.26	0.44	0.48
Manufacturing, nec	0.50	0.62	0.49	0.44	0.86	0.50	0.50

Table 3 (continued)

STANDARD DEVIATION OF LOG LABOR PRODUCTIVITY

	ARG	BRA	CHI	COL	VEN	EST	LAT	ROM	SLN	KOR	IND	TWN
Total manufacturing (weighted avg)	**0.89**	**1.00**	**0.81**	**0.88**	**0.98**	**0.89**	**1.03**	**1.06**	**0.77**	**0.73**	**1.07**	**0.74**
Food products, beverages and tobacco	0.95	1.02	0.86	1.02	1.06	0.97	0.96	1.11	0.72	0.93	1.21	0.81
Textiles, textile products, leather and footwear	0.90	1.01	0.71	0.81	0.86	0.82	1.07	1.06	0.79	0.76	1.01	0.80
Wood and products of wood and cork	0.89	0.94	0.77	0.76	0.86	0.90	1.03	1.13	0.80	0.70	1.00	0.69
Pulp paper, paper products, printing and publishing	0.79	0.96	0.83	0.81	1.01	0.86	1.04	1.09	0.67	0.73	1.05	0.68
Coke refined petroleum products and nuclear fuel	1.11	1.01	1.55	0.96	1.23			1.03	0.41	1.02		
Pharmaceuticals	0.84	0.98	0.63	0.85	0.78	1.18	1.15	0.77	0.93		1.25	0.82
Chemicals excluding pharmaceuticals	0.98	0.98	0.82	0.94	1.05	1.10	1.13	1.10	0.78	0.83	1.41	0.87
Rubber and plastics products	0.80	1.01	0.70	0.80	0.77	0.85	1.09	1.14	0.74	0.65	1.13	0.72
Other non-metallic mineral products	0.82	0.96	0.93	0.94	0.97	0.99	1.09	1.03	0.72	0.77	1.00	0.72
Basic metals	0.86	0.97	1.21	1.10	1.10	0.14	1.53	1.19	0.70	0.81	1.18	0.85
Fabricated metal products except machinery and equipment	0.86	1.07	0.76	0.77	0.89	0.87	1.01	1.07	0.77	0.66	1.05	0.68
Machinery and equipment n.e.c.	0.87	0.97	0.70	0.75	0.91	1.12	1.11	0.92	0.79	0.59	1.14	0.70
Office accounting and computing		1.04	0.46	0.59		1.09	1.14	1.20	0.72	0.79		0.75
Electrical machinery and apparatus nec	0.77	1.05	0.78	0.83	0.92	1.17	0.90	1.03	0.75	0.69	1.15	0.74
Radio, television and communication equipment	1.02	0.99	0.90	0.81	0.29	0.93	1.23	1.33	0.79		1.11	
Medical precision and optical instruments	0.74	1.05	0.51	0.75	1.01	0.95	0.97	1.12	0.77	0.66		0.71
Motor vehicles, trailers and semi-trailers	0.78	0.95	0.76	0.88	0.96	0.61	1.29	0.85	0.92	0.62	1.06	0.71
Building and repairing of ships and boats					1.12	1.05	1.02	0.95	0.62		0.93	0.78
Railroad equipment and transport	1.00	1.08			0.68			0.92	0.73		1.14	0.78
Aircraft and spacecraft			0.92					1.12	1.26			
Manufacturing, nec	0.74	0.99	0.75	0.76	0.86	0.77	0.86	1.12	0.75	0.68	0.75	0.72

Table 4.

STANDARD DEVIATION OF MFP

	FIN	FRA	NLD	UK	USA
Total manufacturing	**1.77**	**0.20**	**0.15**	**0.19**	**0.34**
Food products, beverages and tobacco	1.92	0.18	0.15	0.20	0.34
Textiles, textile products, leather and footwear	1.80	0.34	0.17	0.19	0.49
Wood and products of wood and cork	1.84	0.17	0.12	0.19	0.37
Pulp paper, paper products, printing and publishing	2.11	0.21	0.14	0.24	0.39
Coke refined petroleum products and nuclear fuel	2.30	0.09	0.13		0.27
Pharmaceuticals	1.87	0.24	0.17	0.25	0.37
Chemicals excluding pharmaceuticals	1.79	0.18	0.15	0.22	0.34
Rubber and plastics products	1.65	0.13	0.14	0.17	0.32
Other non-metallic mineral products	1.54	0.19	0.17	0.22	0.32
Basic metals	2.16		0.10	0.18	0.34
Fabricated metal products except machinery and equipment	1.56		0.15	0.20	0.35
Machinery and equipment n.e.c.	1.62	0.14	0.14	0.19	0.37
Office accounting and computing	1.58		0.16	0.24	0.47
Electrical machinery and apparatus nec	1.90	0.16	0.16	0.18	0.31
Radio, television and communication equipment	1.81	0.19	0.18	0.21	0.44
Medical precision and optical instruments	1.75	0.18	0.17	0.20	0.33
Motor vehicles, trailers and semi-trailers	1.68	0.30	0.11	0.18	0.30
Building and repairing of ships and boats	2.31		0.13	0.23	0.32
Railroad equipment and transport	1.81		0.12	0.21	0.25
Aircraft and spacecraft			0.16	0.19	0.29
Manufacturing, nec	1.55	0.20	0.16	0.20	0.33

Table 4 (continued)

STANDARD DEVIATION OF MFP

	BRA	CHI	COL	VEN	EST	ROM	SLV
Total manufacturing	**0.64**	**0.55**	**0.50**	**0.73**	**0.36**	**0.49**	**0.39**
Food products, beverages and tobacco	0.99	0.56	0.49	0.76	0.24	0.40	0.28
Textiles, textile products, leather and footwear	0.64	0.54	0.52	0.64	0.45	0.68	0.56
Wood and products of wood and cork		0.60	0.53	0.66	0.32	0.50	0.40
Pulp paper, paper products, printing and publishing	0.85	0.59	0.44	0.65	0.46	0.71	0.35
Coke refined petroleum products and nuclear fuel	0.62	0.44	0.41	1.20		0.37	0.20
Pharmaceuticals	0.69	0.41	0.61	0.80	0.61	0.49	0.60
Chemicals excluding pharmaceuticals	0.58	0.57	0.58	0.98	0.43	0.39	0.36
Rubber and plastics products		0.48	0.47	0.62	0.44	0.50	0.38
Other non-metallic mineral products	0.60	0.77	0.66	0.96	0.42	0.50	0.48
Basic metals	0.93	0.50	0.53	0.88		0.35	0.24
Fabricated metal products except machinery and equipment	0.49	0.50	0.54	0.62	0.43	0.51	0.40
Machinery and equipment n.e.c.	0.61	0.45	0.51	0.44	0.42	0.50	0.38
Office accounting and computing	2.26	0.71	0.45		0.13	0.44	0.26
Electrical machinery and apparatus nec	0.72	0.67	0.51	0.60	0.31	0.52	0.42
Radio, television and communication equipment	0.85	0.92	0.52	0.41	0.85	0.54	0.48
Medical precision and optical instruments	0.99	0.50	0.65	0.51	0.46	0.56	0.46
Motor vehicles, trailers and semi-trailers	0.74	0.53	0.38	0.57	0.07	0.40	0.24
Building and repairing of ships and boats				0.89	0.36	0.72	0.36
Railroad equipment and transport	0.45			0.70		0.37	0.49
Aircraft and spacecraft		0.72				0.90	0.25
Manufacturing, nec	0.77	0.48	0.64	0.53	0.33	0.51	0.43

Table 5 Business sector regulatory indicators

Country	Financial development[1]	Rigidity of employment[2]	Starting a business (days)	Enforcing a contract (days)	Closing a business (years)
Denmark	0,73	17	5	0,5	3,0
Finland	1,04	48	14	0,6	0,9
France	1,22	56	8	0,9	1,9
Germany	1,29	44	24	1,1	1,2
Italy	0,7	54	13	3,3	1,2
Netherlands	2,36	42	10	1,1	1,7
Portugal	0,83	51	8	1,4	2,0
UK	2,26	14	18	0,6	1,0
USA	1,8	0	5	0,8	1,5
Argentina	0,4	41	32	1,4	2,8
Chile	1,27	24	27	1,3	5,6
Colombia	0,37	27	44	3,7	3,0
Estonia	0,56	58	35	0,8	3,0
Hungary	0,46	34	38	0,9	2,0
Indonesia		44	97	1,6	5,5
Korea	1,86	34	22	0,6	1,5
Latvia		59	16	0,7	3,0
Mexico	0,51	38	27	1,1	1,8
Romania	0,1	51	11	0,9	4,6
Slovenia	0,34	57	60	3,7	2,0
Taiwan (China)		56	48	1,4	0,8
Average	1,01	40	27	1,36	2,38
Standard deviation	0,68	16	22	0,97	1,40

1. The synthetic indicator of financial development is the simple average of two sub-indicators: i) the ratio of domestic credit to the private sector to GDP (from the IMF International Financial Statistics); and ii) the ratio of stock market capitalization to GDP (from Standard and Poor's and World Bank's World Development Indicators). See Beck, Demirgurc-Kunt and Levine (2000).
2. The average of three indicators: difficulty of hiring a new worker (Difficulty of Hiring Index), restrictions on expanding or contracting the number of working hours (Rigidity of Hours Index), difficulty and expense of dismissing a redundant worker (Difficulty of Firing).

Sources: World Bank, Doing Business Indicators, 2007.

Table 6: Calibrated Model Results for Alternative Institutional Settings

Measure	(1) Non-Distorted	(2) Uncorrelated Scale	(3) Uncorrelated Scale	(4) Correlated Scale	(5) Correlated Scale	(6) Uncorrelated Factor Mix
	Ex ante Institutional Parameters					
Std(Distortions)	0.00	0.14	0.29	0.32	0.45	0.29
Corr(Distortions, log(TFPQ))	0.00	0.00	0.00	0.20	0.28	0.00
	Moments from Plant-level Productivity Distributions					
Diff unweighted mean log(RLP)	0.00	0.06	0.10	-0.13	-0.20	0.18
Std(log(RLP))	0.31	0.31	0.31	0.24	0.23	0.30
OP cross term log(RLP)	0.21	0.18	0.16	0.08	0.04	0.20
Diff unweighted mean log(TFPR)	0.00	0.00	-0.01	-0.21	-0.29	0.03
Std(log(TFPR))	0.28	0.30	0.33	0.32	0.33	0.31
OP cross term log(TFPR)	0.25	0.26	0.24	0.21	0.17	0.27
Diff unweighted mean log(TFPQ)	0.00	0.01	-0.01	-0.17	-0.24	0.05
Std(log(TFPQ))	0.58	0.59	0.61	0.56	0.54	0.61
OP cross term log(TFPQ)	0.73	0.70	0.69	0.52	0.45	0.73
Corr(log(RLP), log(labor))	0.86	0.77	0.68	0.50	0.38	0.84
Corr(log(TFPR), log(revenue))	0.90	0.88	0.82	0.76	0.65	0.89
Corr(log(TFPQ), log(output))	0.98	0.97	0.95	0.92	0.89	0.97
	Key Aggregate Moments					
Capital Share of Final Output	0.22	0.24	0.29	0.30	0.35	0.28
Overhead Share	0.12	0.11	0.11	0.11	0.10	0.10
Share of entrants that survive	0.47	0.38	0.31	0.50	0.46	0.30
Entry cost share of Output	0.10	0.12	0.14	0.12	0.14	0.12
Diff log(consumption)	0.00	-0.17	-0.41	-0.26	-0.51	-0.21
Diff log(Agg Labor Productivity)	0.00	0.03	0.05	-0.28	-0.39	0.18

Notes: Diff refers to difference from benchmark non-distorted mean of relevant statistic.

Figure 1. Comparison of dispersion of labor and MFP productivity -- manufacturing, 1990s

(standard deviation in log productivity)

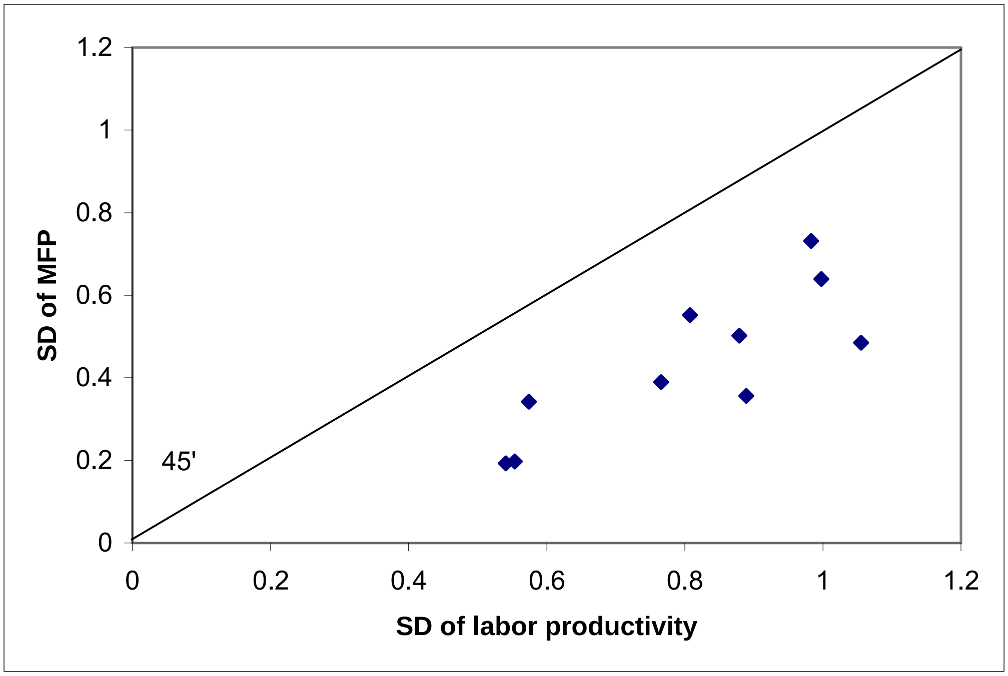
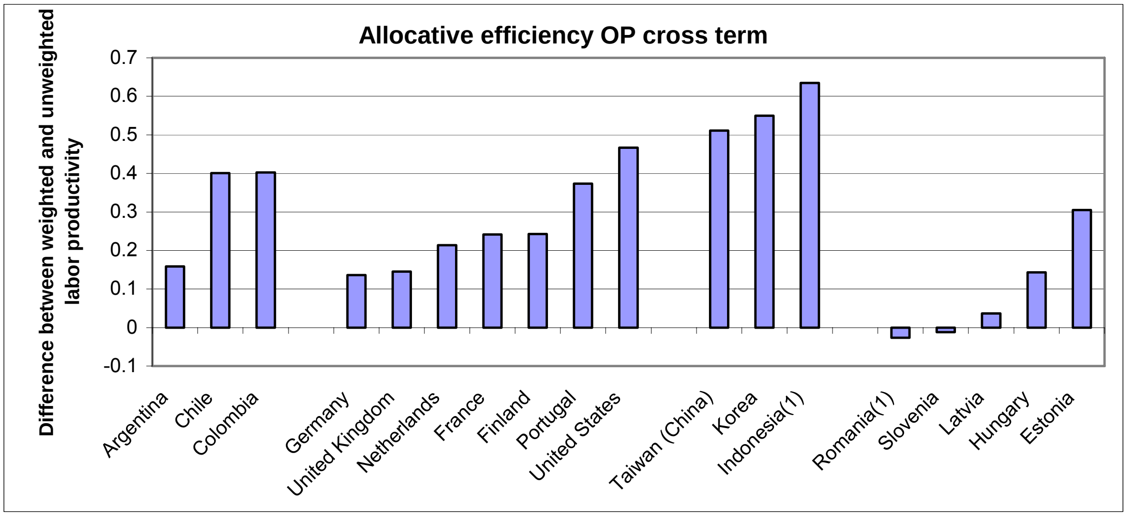


Figure 2.

Allocative efficiency (Olley Pakes decomposition -- cross term)
(weighted averages of industry level cross terms from OP decomposition)



1. Based on the three-year differences

Figure 3.

Evolution of allocative efficiency during the transition -- Eastern Europe, manufacturing
(weighted averages of industry level cross terms from OP decomposition)

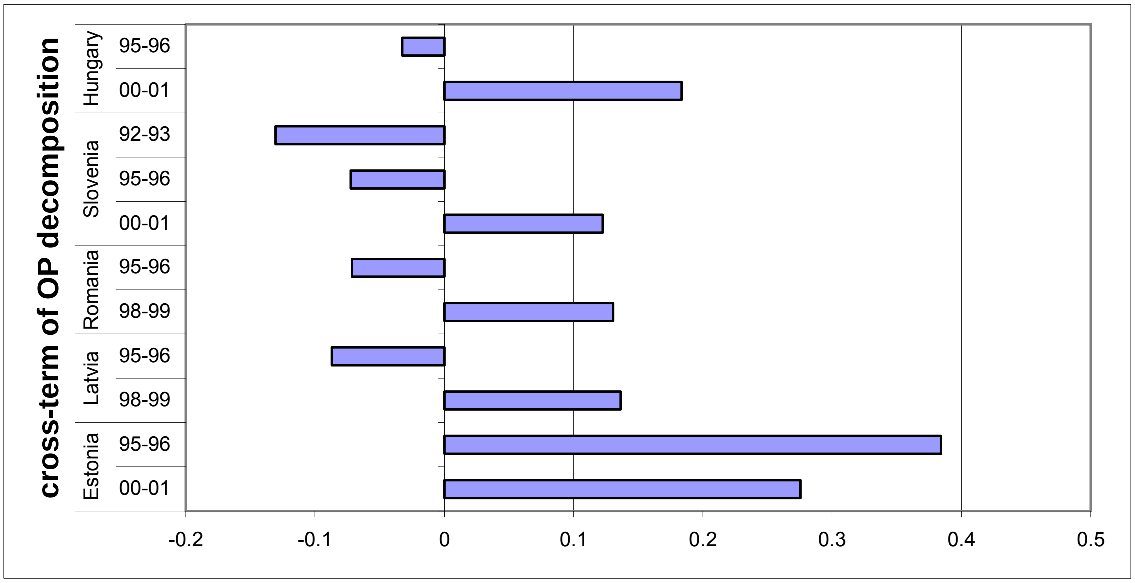
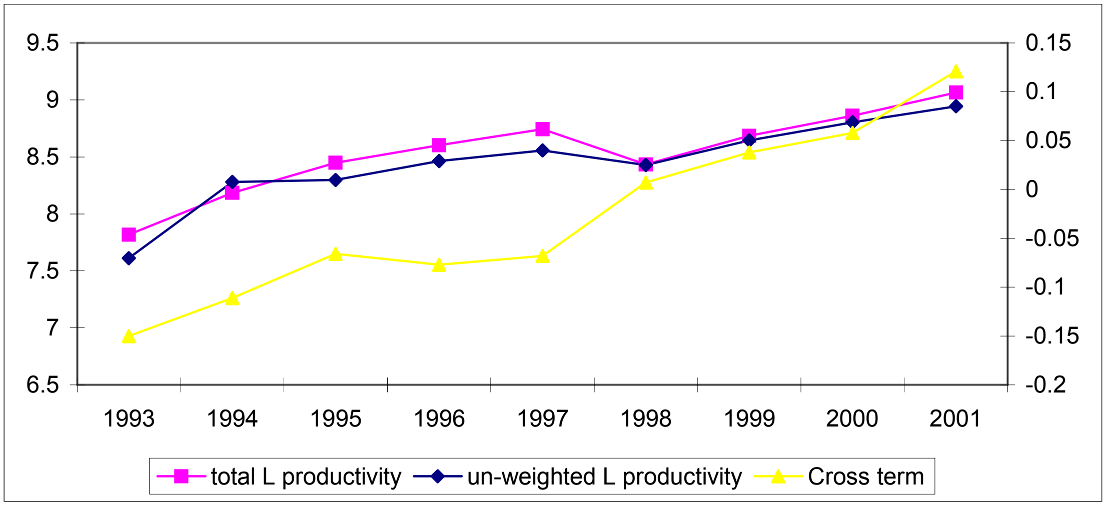


Figure 4.

Slovenia: allocative efficiency over the transition
(cross-term of the Olley Pakes decomposition, manufacturing)



Hungary: allocative efficiency over the transition
(cross-term of the Olley Pakes decomposition, manufacturing)

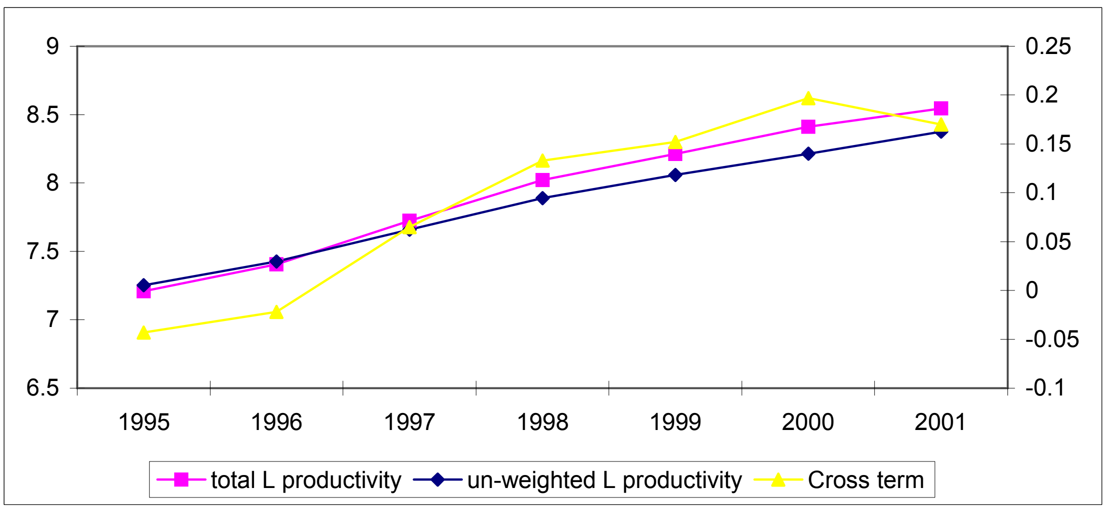
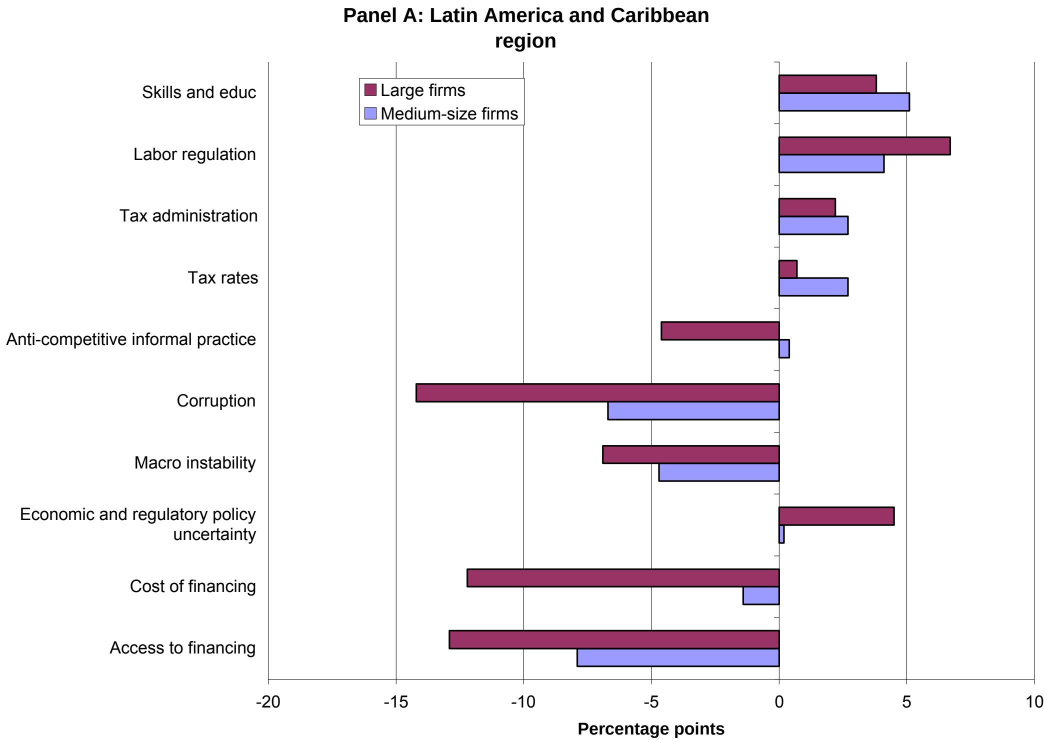


Figure 5.

Perceived constraints to the operation and growth potential by firm size
medium-size (20-100) and large firms (100+) versus small firms (fewer than 20 employees)



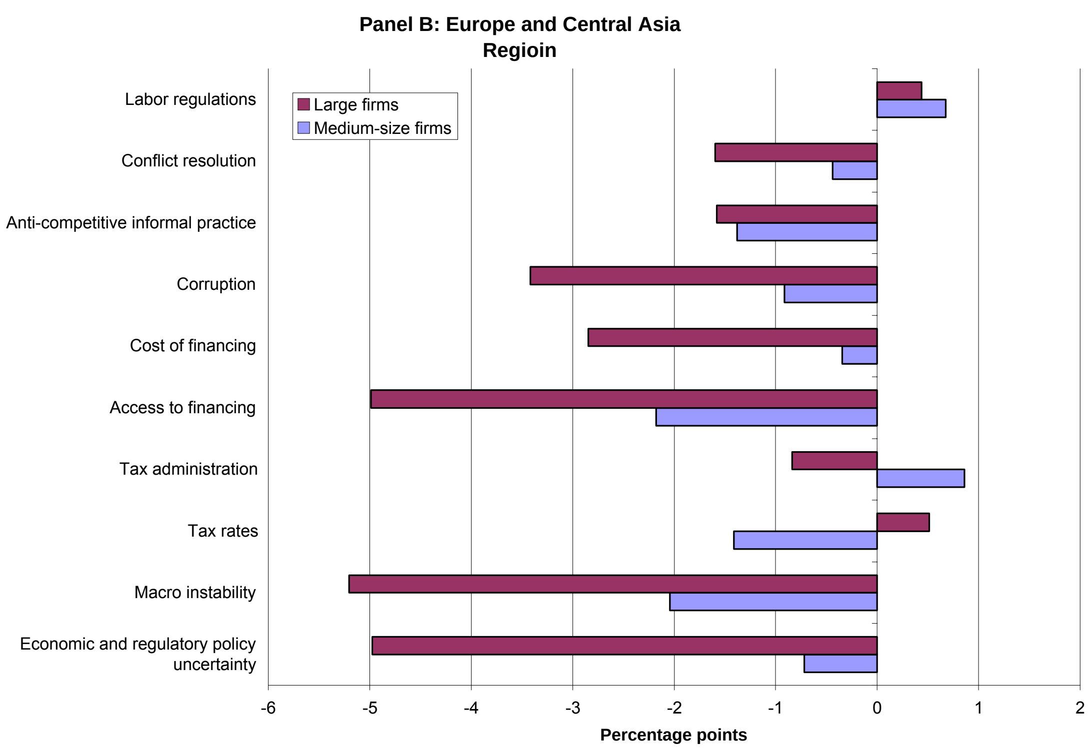


Figure 6 The Relationship Between Labor Productivity and Employment

No distortion Case

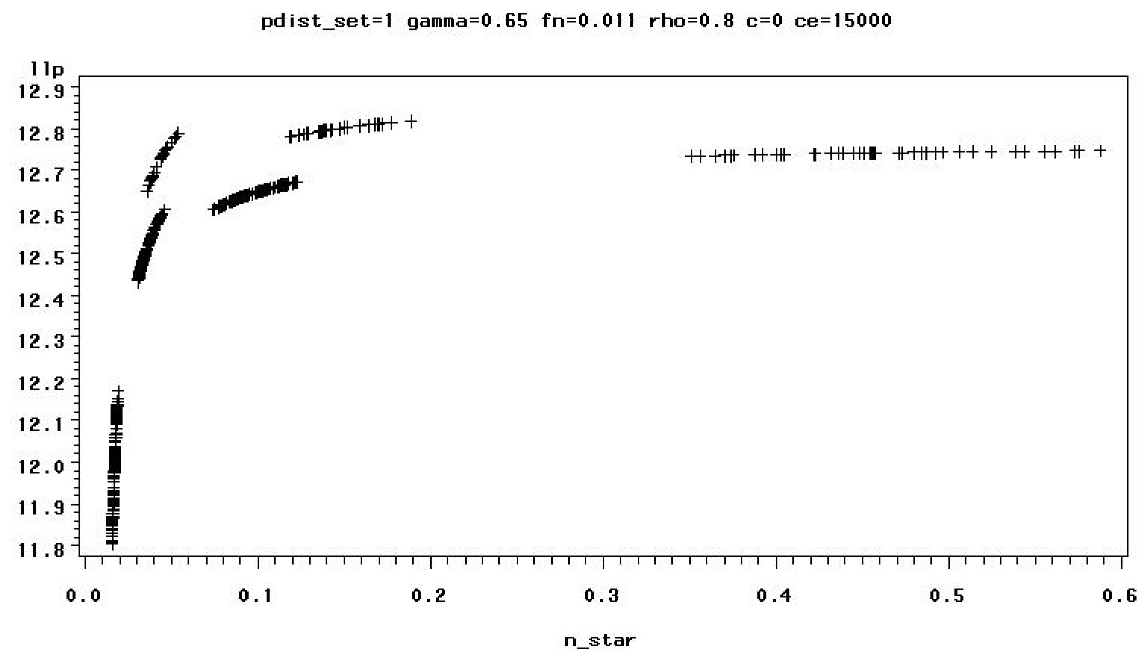


Figure 7 The Relationship Between Distortions and Labor Productivity

Random Scale Distortion

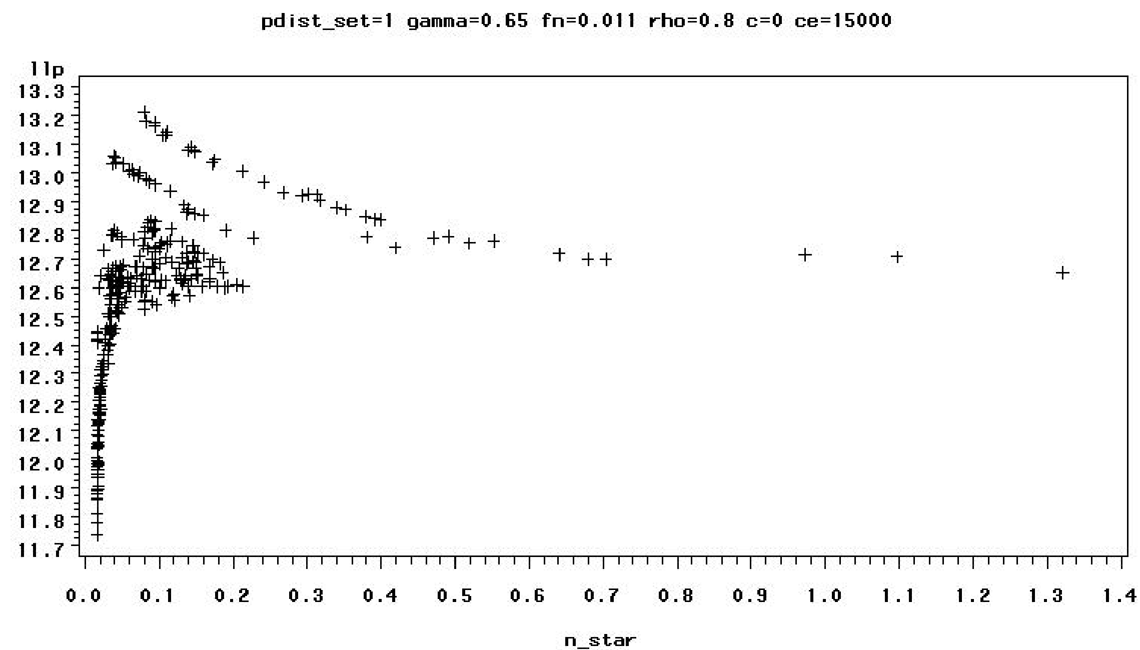


Figure 8 The Relationship Between Distortions and Labor Productivity

Correlated Scale Distortion Case

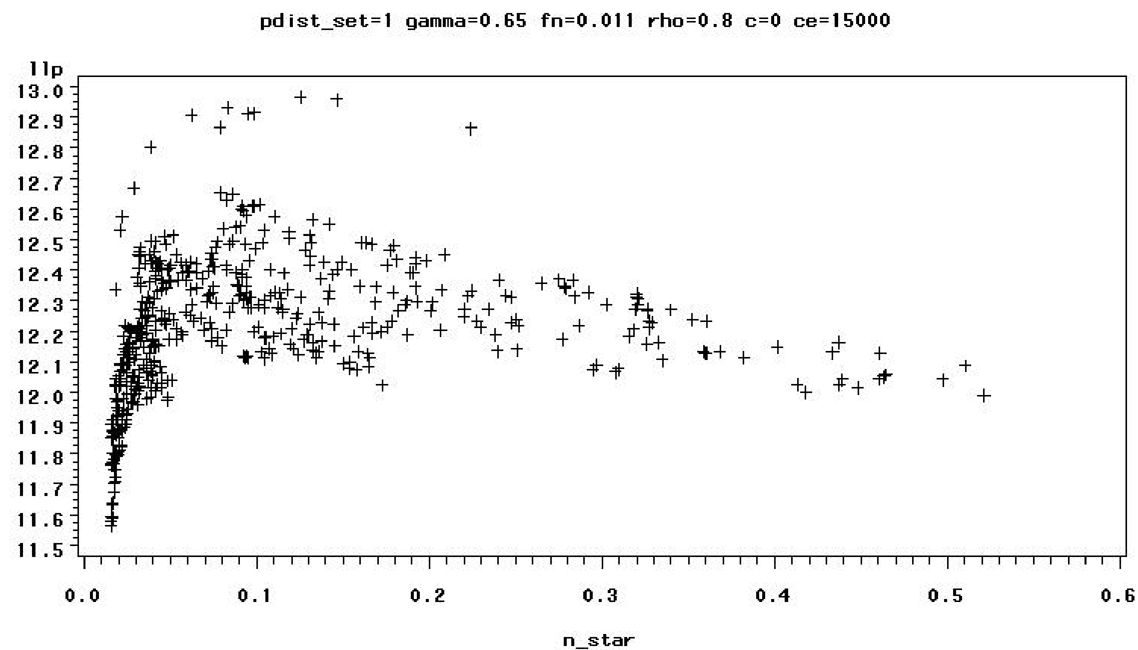
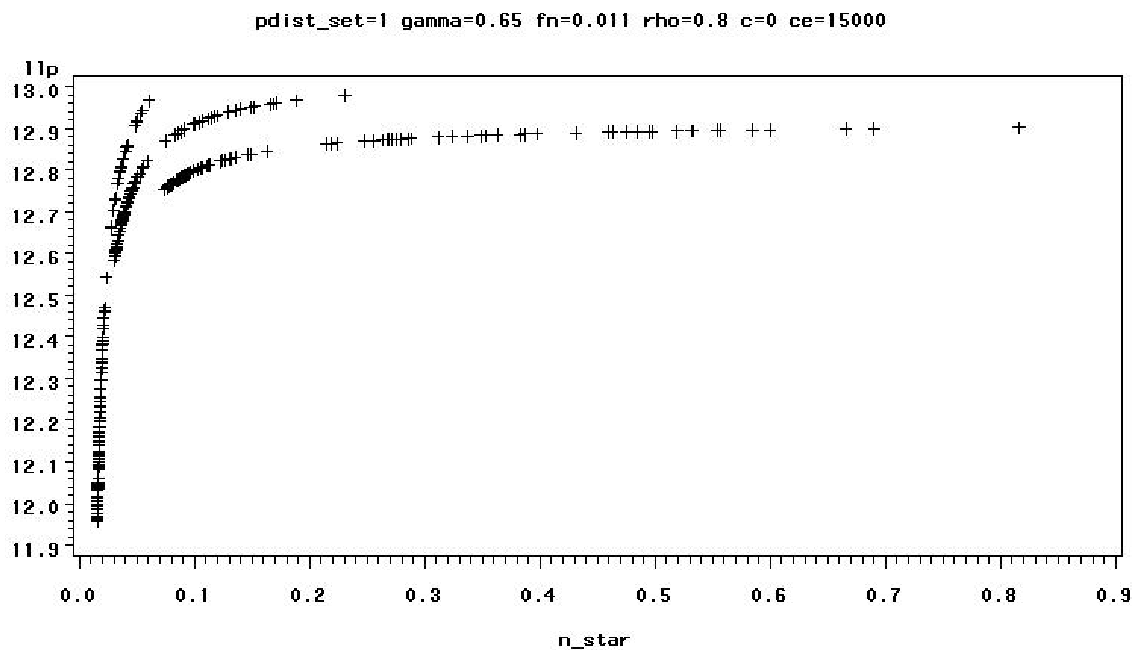


Figure 9 The Relationship Between Distortions and Labor Productivity

Random Factor Mix Distortion



Annex Table 1

Distribution of firms by size -- Industry-level data -- manufacturing
(ratio of the mean size of fourth to the first quartile of the distribution of firms)

	ARG	BRA	CHI[1]	COL[1]	EST	FIN	FRA	GBR	HUN
Total manufacturing	36.5	65.3	15.5	24.0	51.9	31.2	39.3	102.4	
Food products, beverages and tobacco	59.6	81.1	15.1	29.4	55.3	30.3	18.6	123.0	133.6
Textiles, textile products, leather and footwear	31.9	55.2	14.5	24.1	55.3	28.8	38.2	68.8	117.0
Wood and products of wood and cork	20.8	36.1	13.1	13.6	25.6	22.7	13.8	38.9	51.3
Pulp paper, paper products, printing and publishing	42.5	53.2	18.7	21.2	31.3	29.8	32.2	70.5	58.9
Coke refined petroleum products and nuclear fuel	168.4	156.7	23.5	73.9	25.0	67.0	327.6	421.7	5272.5
Pharmaceuticals	49.3	145.0	11.3	33.0	59.5	40.5	56.5	466.2	552.4
Chemicals excluding pharmaceuticals	98.0	100.2	16.7	27.4	137.2	48.6	67.9	197.6	168.1
Rubber and plastics products	26.9	56.8	12.0	18.9	24.8	27.7	30.6	99.7	66.8
Other non-metallic mineral products	47.3	38.9	15.8	27.9	55.7	30.2	33.6	127.5	105.4
Basic metals	61.5	118.6	46.6	45.1	37.8	113.8		134.1	246.3
Fabricated metal products except machinery and equipment	20.7	37.6	11.2	16.5	26.3	19.1		50.6	55.0
Machinery and equipment n.e.c.	27.3	73.5	15.5	14.8	45.2	39.9	55.1	82.1	74.7
Office accounting and computing	19.2	123.5	6.7	8.8	13.9	97.0		174.8	74.6
Electrical machinery and apparatus nec	34.1	97.4	13.7	21.9	83.3	49.9	82.2	141.0	183.7
Radio, television and communication equipment	74.0	136.2	15.9	19.9	139.6	60.7	87.3	196.2	187.5
Medical precision and optical instruments	25.1	73.2	8.7	12.3	39.0	26.4	38.1	140.8	64.8
Motor vehicles, trailers and semi-trailers	60.9	183.9	13.4	25.2	52.2	47.7	129.0	310.3	253.5
Building and repairing of ships and boats	16.8	48.8			114.2	65.8		173.7	39.9
Railroad equipment and transport	27.9	96.5			58.5	51.0		374.7	127.7
Aircraft and spacecraft	125.7	191.7	20.7			137.6		778.8	150.7

1. Firms with 10 or more employees.
2. Firms with 15 or more employees and sample of smaller units.