Cross Country Differences in Productivity: The Role of Allocative Efficiency

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Abstract

There is a growing body of evidence suggesting that healthy, market economies exhibit both static and dynamic allocative efficiency, whereby more productive businesses have a larger market share and reallocation of outputs and inputs within sectors shifts resources from the less to more productive businesses (e.g. (Bartelsman, Haltiwanger, and Scarpetta 2004a);(Foster, Haltiwanger, and Krizan 2001)). By contrast, in a frictionless economy there are no welfare or productivity gains to be obtained from resource reallocation (Levinsohn and Petrin 2006). In this paper, we consider models that feature taste and technology such that a market with free entry sustains firms operating within a wide range of productivity (e.g, (Restuccia and Rogerson 2004), and (Hsieh and Klenow 2006)). We then investigate to what extent distortions in signals to decision makers generate model outcomes that track (may help explain?) patterns of resource allocation and productivity observed across countries, sectors and over time.

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Introduction

There is a growing body of evidence suggesting that healthy, market economies exhibit both static and dynamic allocative efficiency, whereby more productive businesses have a larger market share and reallocation of outputs and inputs within sectors shifts resources from the less to more productive businesses (e.g.(Bartelsman, Haltiwanger, and Scarpetta 2004a);(Foster, Haltiwanger, and Krizan 2001)). In an accounting sense, the contribution of reallocation to overall productivity is sizeable, mainly because of the large differences in productivity performance across firms even in narrowly defined industries.. Empirical evidence suggests, for example, that the difference in total factor productivity between the 90^{th} and the 10^{th} percentiles within narrowly defined industries is about 99 log points in the United States, and for labor productivity is about 140 log points (see, e.g., (Syverson 2004a). This wide dispersion in productivity provides considerable scope for reallocation in promoting higher aggregate productivity and growth.

The evidence of large dispersion in firm productivity and, in turn, of a sizeable contribution of allocative efficiency in market economies raises a variety of questions. The coexistence in narrowly-defined industries of firms with very different productivity performance even in healthy, market economies is consistent with the idea of substantial frictions preventing resources from being immediately allocated to the highest valued use. Such frictions might arise from many factors. It may be that the frictions represent the costs of adjustment – either in the form of entry and exit costs, or adjustment costs in reallocating factors of production such as capital and labor (World Bank, *Doing Business, 2006)*. The latter might involve a range of costs including the search and matching frictions that have been the focus of much of the recent literature on studying the dynamics of the labor market (see e.g. (Davis, Haltiwanger, and Schuh 1996);(Restuccia and Rogerson 2004); (Hsieh and Klenow 2000; Hsieh and Klenow 2006)). There may be static frictions that imply persistent productivity differences across producers in seemingly narrowly defined sectors. Product differentiation within sectors due to local markets is one such factor. For example, (Syverson 2004a) explored the role of local markets for the U.S. concrete industry and found that variation in the market density across local markets significantly accounts for variation in the dispersion of productivity and prices across these markets.

Static and dynamic frictions partly depend on market characteristics and technological factors. However, frictions can also be driven by policy and institutions that affect market competition and adjustment costs. While these issues are hardly resolved for advanced economies, they assume a larger role in emerging and transition economies. These countries tend to have institutional factors that create additional distortions to the allocative process. There are many factors that may underlie such additional distortions. Implicit or explicit subsidies to favored incumbents might be one source of distortion. Excessive regulations that make the cost of doing business inefficiently high (e.g., start up costs) is another factor. The infrastructure for doing business (e.g., communications and transportation infrastructure) may weaken an efficient allocation process. Moreover, graft and corruption that yields uneven application of rules and regulations also hurting allocative efficiency. All of these factors worsen different aspects of the investment climate and affect the performance of private firms. In this paper, we emphasize their effects of dispersion in business climate conditions across producers *within* each country, since we are especially interested in the role of allocative efficiency.

The basic working hypothesis is that frictions play an important role in the allocative efficiency and, through this channel, to productivity and output growth. While some of these frictions are inherent even in well-developed market economies, others are affected by policy and institutional settings and thus could be tackled by appropriate reforms. The evidence of large dispersion in allocative efficiency even within OECD countries provides support to this claim. This is not a new hypothesis, and others have explored its implications in a variety of theoretical and empirical contributions (see e.g.,(Banerjee and Duflo 2004);(Restuccia and Rogerson 2004); and (Hsieh and Klenow 2006)). Our contribution is to quantify the magnitude of allocative efficiency in a sample of industrial, and emerging economies drawing from a harmonized, cross country database with key measures and moments from firm-level data. Using a simple decomposition of industry-level productivity ((Olley and Pakes 1996)), we find evidence of considerable cross country variation in allocative efficiency across countries. For example, we find that in the United States shifting from the existing firm allocation of market shares to one where shares are allocated randomly would yield a 60 percent loss in labor productivity. Moreover, we find significant changes in allocative efficiency over time in the Eastern European countries during their transition to a market economy: market oriented reforms in these countries have led to an increase in allocative efficiency of about 30-50 log points.

However, these empirical decompositions are only suggestive and require some more theoretical underpinning. Accordingly, we develop a simple model that draws heavily on the models of (Restuccia and Rogerson 2004); and (Hsieh and Klenow 2006). We calibrate this model to match the moments from our harmonized data and in particular the moments from the Olley-Pakes (hereafter OP) empirical decomposition. We show that, consistent with our working hypothesis, an increase cross-firm dispersion of distortions yields a decline in allocative efficiency as measured by the OP decomposition. We push this finding further by quantifying the magnitude of distortions that are needed to account for the variation in the observed OP measures, both between and within countries.

By exploring the theoretical underpinnings of the empirical decompositions that have appeared in the literature, we also discuss how distortions can affect different margins of the reallocation process. Consistent with the intuitive explanations of the Olley-Pakes decompositions, we find that distortions tend to reduce the OP cross term – that is to say the covariance of market share and productivity of a given set of market participants. However, there are additional margins impacted by distortions that are, potentially, at least as important. 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 lower the average unweighted productivity of market participants. Second, in a model where potential market participants must pay an entry fee before learning their productivity, distortions will affect the number of new firms that pay entry fees. But 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 consumption (or more generally welfare). The implication of these findings is that while measured allocative efficiency in terms of the OP cross term is a useful indicator it is by far not the only one for quantifying the impact of distortions on market economies.

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 patterns of allocative efficiency as measured by the OP decomposition. Section 4 develops the model of allocative efficiency with distortions in the allocative process. Section 5 calibrates the model numerically to explore the implications of the model in light of the empirical patterns in section 3. Section 6 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.[2] 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 2004b).[3]

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

2 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 uses a smaller sub-set of countries do to data availability.

3 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.

year. The classification into about 40 sectors (roughly the 2-digit level detail of ISIC Rev3) coincides with the OECD Structural Analysis (STAN) database.[4]

For the purposes of this paper, we consider two indicators of dispersion that are particularly relevant. First, we look at the distribution of firm by size across industries and countries. The observed wide, and skewed towards small units, distribution of firm size shows ample room for reallocation of labor. For such reallocation of labor be influence aggregate productivity -- even if only in an accounting sense -- there must be differences in productivity levels across firms. The data indeed allow looking at this second dimension of firm dispersion.

- **Heterogeneity in firm size among incumbents:** Table 1 presents the ratio of the average size of the fourth to the first 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 MFP:** There are also wide differences in firms' productivity performance within manufacturing industries. Table 2 presents the difference between the fourth and first quartile of the log labor productivity. The differences are large: in 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, confirming that where there is more room for innovation and market experimentation there is more heterogeity in firm characteristics and performance. To confirm this, Table 3 and Table 4 present the standard deviation in labor and multifactor productivity respectively for the different manufacturing industries. Moreover, there is a wider dispersion in labor than in MFP for all the countries for which we have data (Figure 1)

4. See www.oecd.org/data/stan.htm

3. Empirical Measures of Allocative efficiency

How does this observed heterogeneity in firm characteristics and performance affect aggregate productivity? To address this question, we look at measures of allocative efficiency by adopting an empirical procedure to decompose the level of productivity within industries 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:

$$P_t = (1/N_t)\sum_i P_{it} + \sum_i (\theta_{it} - \bar{\theta}_t)(P_{it} - \bar{P}_t)$$

where P_t is sectoral productivity, P_{it} is firm-level productivity, θ_{it} is the share of activity for the firm, N_t is the number of businesses in the sector 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 can be decomposed into two terms involving the un-weighted average of firm-level productivity plus a cross term that reflects the cross-sectional efficiency of the allocation of activity. The cross term captures allocative efficiency since it reflects the extent to which firms with higher than average productivity have a greater market share.

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 any 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. A number of studies (e.g., (Eslava et al. 2004), and (Foster, Haltiwanger, and Krizan 2002)) have shown that the patterns of the OP decomposition within a country are similar for labor productivity and total factor productivity when using the same market shares. In the numerically simulated model discussed in the next sections, we also use labor productivity to derive inferences on the impact of distortions on the patterns of allocative efficiency.

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 -- or as we denote "allocative efficiency" 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 allocative efficiency 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, labor productivity would be about 50 logs point smaller if labor were allocated randomly. 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 – if not higher – allocative efficiency 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 within an industry that 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 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 allocative efficiency 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 suitable framework 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 transtion.

Another advantage of examining the OP cross term over time within countries is that the variation in the estimated allocative efficiency can be put in the context of the overall patterns of productivity growth. In other words, changes in allocative efficiency may take place in the context of increasing or decreasing labor productivity. 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, and at a even faster pace in the case of Slovenia. Thus, it would be misleading to draw inferences from Figures 2 and 3 that the OP cross term accounts 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 (with associated concerns about measurement error) and within transition economies at least it has increased substantially over time. In comparing these findings to the existing literature, it is worth noting that Olley and Pakes (1996) found a positive cross term using TFP as the measure of productivity in the U.S. telecommunications industry and that the cross term increased substantially following deregulation in the U.S. telecommunications industry. Eslava et. al. (2006) 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. These findings in the literature along with Figures 2-4 strongly suggest that the OP cross term is capturing allocative efficiency. However, since it is a simple empirical decomposition without structure, this evidence is only suggestive. To help put structure on the results in Figures 2-4, we turn to a model of allocative efficiency and distortions in the next section.

4. A Simple Model of Allocative Efficiency

To guide our analysis of distortions and allocative efficency we develop a simple model drawing heavily from (Restuccia and Rogerson 2004) and (Hsieh and Klenow 2006). 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 2004)).

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

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

where Y_{it} is output for firm in period t, A_i is the firm specific time invariant productivity for firm i, k_{it} is the amount of capital input of firm i at time t, n_{it} is the employment, and f is overhead labor. Decreasing returns is assumed due to some unobserved fixed factor in a manner similar to (Lucas 1978) where like the latter paper it is useful to think about this factor as managerial ability.[5] The decreasing returns insures (as in (Lucas 1978)) 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 product of labor will be set equal to the wage rate, the average product of labor will vary with scale given overhead labor).

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

$$(2)\quad \pi_{it} = A_i(1-\tau_i)(n_{it} - f)^{\gamma-\alpha} k_{it}^{\alpha} - w_t n_{it} - (1-\kappa_i) r_t k_{it}$$

[5] In order to get dispersion, we require some curvature in profits. Here we assume decreasing returns but a reasonable alternative is to assume some degree of market power in, e.g., a differentiated product environment. Hsieh and Klenow (2006) assume the latter. In future drafts we will add a differentiated product structure to explore the role of such a structure for our results.

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 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.

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 firm enters, we assume that firms do not know their production and distortion draws but they know the distribution of these idiosyncratic variables. There is a fixed cost of entry, given by c_e, that firms must pay to enter and to learn their draws from the joint ex ante distribution of productivity and distortions, $G(A,\tau,\kappa)$. Once a firm learns their draws of A_i, τ_i, and κ_i, their values remain constant.

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, 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 and in the steady state, the present discounted value for an incumbent firm *i* ex post is given simply by:

$$(3)\quad W(A_i,\tau_i,\kappa_i) = \pi(A_i,\tau_i,\kappa_i)/(1-\rho)$$

where

$$\rho = (1-\lambda)/(1+R)$$

In turn, the free entry condition is given by:

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

Firms with a low productivity and/or a high scale (or factor mix) distortion draw will exit upon learning their draws if they cannot cover their fixed operating costs. The optimal capital/labor allocation will depend on input prices and the idiosyncratic capital distortion. An operating firm will have capital and employment given by:

$$(5)\quad k_{it}^{*} = \left[\frac{\alpha(1-\tau)A_i\left((1+\kappa)\dfrac{(\gamma-\alpha)r}{\alpha w}\right)^{\gamma-\alpha}}{r(1+\kappa)} \right]^{1/(1-\gamma)}$$

$$(6)\ n_{it}^{*} = f + k_{it}^{*}(1+\kappa)\frac{(\gamma-\alpha)r}{\alpha w}$$

Output and profits for the operating firm are given by the (1) and (2).

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:

$$N_t^d = \int_{A,\tau,\kappa} n_t^{*}(A,\tau,\kappa)\,d\mu(A,\tau,\kappa)$$

where $\mu(A,\tau,\kappa)$ is the ex post joint distribution for operating firms of productivity and distortions. 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:

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

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 is the time zero price of period t consumption, w and r are the period t rental prices of labor and capital measured relative to period t output, and π 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 is pinned down by the discount factor for utility and the capital depreciation rate.

5. Calibration of Model

We explore calibrations of the model in two steps. First, we choose some "reasonable" parameters for the model and explore its numerical properties. This analysis helps us to understand the interactions in the model and the role of distortions. Second, we push this calibration harder by attempting to match key moments from the micro data as discussed in Section 3.

For our initial numerical explorations, we select:

- $\gamma = 0.9$,
- $\alpha = 0.1$,
- $\lambda = .10$, this is consistent with evidence f exit rates in the United States and other OECD countries (Bartelsman *et al.* 2004)
- R=.03, and $\delta = .12$, consistent with long run real interest rates in OECD countries and typical depreciation rates from national accounts.
- f=0.2 ,log(c_e)=11.92,
- Mean(log(A)) = 10.57
- Std Dev (log(A)) = 0.34

The latter are moments associated with the ex ante distribution G(A,τ,κ). These parameters are roughly consistent with the micro evidence for the U.S. For purposes of calibration and estimation, we start with the U.S. as a base case and then ask whether we can account for the evidence across countries as presented in Section 3 with varying the degree of distortions. For distortions, we consider four different cases:

(i) A no distortion case where $\tau = 0$, and $\kappa = 0$,

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

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

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

Table 5 shows the results from these simulations. For the base case (top row) without distortions, the OP cross term using labor productivity (where weights are employment) and total factor productivity (where weights are the composite input) is positive reflecting positive allocative efficiency in a market economy without distortions. Note, however, that there is a much smaller dispersion of LP relative to TFP. Even with overhead labor, there is a tendency for the average labor productivity to be equalized.

In our scenario with distortions that have ex ante zero mean, or with zero mean distortions that are uncorrelated with productivity, we obtain that, through the selection process, there is a non random, non mean zero ex post distortions. 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).[6]

The adverse consequences of these distortions can be seen on several margins. For the uncorrelated scale distortion case we see lower average labor productivity and average TFP and lower OP cross term for both labor productivity and TFP. We also see much lower survival which implies too much churning and paying of entry costs relative to the non-distorted economy. All of these factors contribute to lower consumption. For the uncorrelated factor mix distortion case, we see relatively little impact on OP terms and unweighted productivity. Indeed unweighted labor productivity increases. Instead what we see is that capital labor ratio is far too high relative to non-distorted economy. In this case, the economy is induced to hold too much capital given implied equilibrium factor price ratio. Survival is too low relative to the non-distorted economy. In combination, the high use of capital and the low survival contribute to very low consumption. Note as suggested above that the factor mix distortion case should be more interpreted as a capital-labor distortion. Thus, economies with distortions to the capital-labor ratio in favor of capital will have labor productivity that is distortedly too high given high capital-labor ratio. For the correlated scale distortion case, we see large impacts on unweighted TFP and OP cross term for TFP. We also see large impacts on unweighted labor productivity and OP cross term. In this case, both who stays in and allocation of those that are participants is distorted substantially. Interestingly, overall survival is roughly the same as in the non-distorted economy but the mix of who survives is highly distorted. Given that survival rates are about the same as in the non-distorted economy, the distortion shows up clearly in OP cross terms for both TFP and labor productivity. This makes sense as OP cross term captures misallocation for a given

[6] 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 (2006) view these distortions as distortions not taxes while Restuccia and Rogerson (2003) model these distortions as taxes. The latter is relevant for the welfare/consumption impact as Restuccia and Rogerson (2003) make a lump sum transfer that could be positive or negative depending on the tax revenue.

set of participants. In this correlated case, all of these factors (i.e., impact on survival, misallocation of who survives, and misallocation of activity amongst survivors) contribute to lower consumption.

To provide further perspective on these simulations, Figures 5-8 present scatterplots of the relationship between labor productivity and employment for the alternative simulated distributions of businesses. In Figure 5, we present the no-distortion case and observe a strong positive and systematic relationship between labor productivity and size. Underlying this pattern is that firms with higher TFP hire more workers and exhibit higher labor productivity at a decreasing rate given the decreasing returns and overhead labor. Figure 6 shows the pattern for the uncorrelated scale distortion case. We observe a much less systematic relationship between labor productivity levels and employment. Moreover, the range of labor productivity and size is much larger than in Figure 5, so we see more dispersion in both labor productivity and size. Figure 7 shows the pattern for the uncorrelated factor mix case. Interestingly in this case there is a strong positive relationship between labor productivity and size as in the non-distorted case. However, the problem here is not so much this covariance but rather the distortedly high capital-labor ratio. Figure 8 shows the correlated scale distortion case. Here the misallocation for survivors is apparent as well as the greater dispersion in labor productivity and size relative to the non-distorted economy.

These simulations are suggestive but still there is still a gap between key features of the simulations and moments from the actual data. For one, while the simulations produce substantial and systematic variation in OP cross terms due to distortions, the variation in the above simulations in the OP cross terms is substantially lower than observed in the actual data. Recall that in countries like U.S. the OP cross term is almost 0.6 while in some transition economies it is negative. A number of factors may be at work here. Under the parameterizations under consideration, ex ante dispersion in TFP is substantial (and similar to that observed in say U.S.) but ex post dispersion in TFP in the non-distorted economy is much lower given selection. Getting a model to have a large dispersion in TFP ex post requires more frictions. Candidate frictions here include: (i) product differentiation as in (Hsieh and Klenow 2006); (ii) learning so that some of the dispersion reflects young businesses that have not yet learned they have low productivity; (iii) adjustment costs. Note that all of these factors can help contribute to dispersion in TFP and labor productivity. We think all of these factors should be considered in this context although we note that consideration of any one of them raises additional issues. For example, with differentiated products it is important to distinguish between measured TFP and physical TFP since typical measured TFP will include price variation (e.g., (Syverson 2004b),and Foster, Haltiwanger and Syverson (2006)).

In considering these issues and in interpreting the results in the data vs. the simulations, it is important to emphasize that dispersion in TFP and labor productivity is critical for OP cross terms for both distorted and non-distorted economies. For non-distorted economies, dispersion is critical to obtain positive and large OP cross terms. Mechanically, the OP cross term can only be large and positive if there are large gaps in productivity between the large and small market share plants. For distorted economies, it would seem to be relatively straightforward to reduce the OP cross term with sufficient distortions. That is, one might argue that OP cross term would seemingly be driven to zero in an environment where distortions just create noise in allocation. The fallacy in this argument is that distortions impact not only allocation but selection – as we found in our simulations distortions impact both the amount of selection and the mix of selection. Thus, it may be that the OP cross term does not fall so much as instead the amount of mix of selection is impacted by distortions.

6. **Concluding Remarks**

As taught in principles of economics classes, market economies provide incentives for an efficient allocation of resources. Empirically, we have learned that well-developed market economies exhibit patterns of allocation consistent with shifting resources to more productive businesses, but the ongoing allocative process is complex and dynamic. A growing body of empirical evidence suggests substantial dispersion in measures of both TFP and labor productivity even within narrowly defined sectors. There is also evidence that more productive businesses tend to be larger than less productive ones. Moreover, the latter is an ongoing process with resources continually being reallocated at a high pace away from less productive to more productive businesses.

The observed dispersion of productivity within narrowly defined sectors and the ongoing reallocation dynamics imply that even in healthy market economies there are substantial frictions in allocating resources to their highest valued use. Put simply, there is no free lunch in the efficient allocation of resources – substantial time and resources are spent in market economies in the allocation process.

In countries with stringent regulations in goods and labor markets – and in particular in the transition economies of Eastern Europe -- these allocation dynamics are arguably further complicated. In particular, the presence of scale or mix distortions prevents resources from being allocated efficiently. In this paper, we explore the associated working conjecture that differences in the level of productivity across countries and over time can be accounted for by such differences in the distribution of distortions. We follow the recent literature by emphasizing that the distortions in industrial, but especially in emerging and transition economies may have an important idiosyncratic component.

Based upon a novel cross country dataset with harmonized statistics on the productivity and size distributions of firms within industries across countries, we present evidence of significant sizeable distortions in allocative efficiency across countries and industries. Using an accounting measure of allocative efficiency, we find for example that that average labor productivity in the manufacturing sector of the United States would be approximately 50 percent lower if labor was allocated randomly as opposed its actual allocation. In transition economies, we find that the accounting measure of allocative efficiency was much smaller (even negative) in the 1990s, but has been increasing rapidly during the transition to a market economy.

With these findings as a backdrop, we build a model drawing heavily from the literature on the role of distortions in the allocative process. We introduce two possible distortions: a *scale* distortion that affects the size the business; and a *factor mix* distortion that affects its factor input composition. In calibrating the model, we show that both distortions can qualitatively generate the patterns of allocative efficiency observed in our accounting decompositions. However, we also find that distortions impact more margins than one might capture on the basis of the accounting decompositions. For example, we find that distortions impact not only the allocation amongst survivors but also who survives and how much churning there is as firms learn about their productivity. These other margins are very important in quantifying the adverse impact of distortions in the economy.

We also note that precisely because other margins do matter in shaping the effects of distortions, our simulated model cannot fully match some key aspects of the firm dispersion observed in the actual data. With our simulated distortions alone, for example, it is a challenge to match the wide dispersion in productivity observed in the data. One of the reasons is indeed that in the actual data we only observe the allocation among survivors, while distortions also affect their selection. We speculate that to match the actual moments we would require models with a richer menu of frictions than the simple model we consider in this paper.

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