

Cross-Country Differences in Productivity: The Role of Selection and Allocation

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Abstract

This paper combines different strands of the productivity literature to investigate the effect of idiosyncratic (firm-level) policy distortions on aggregate outcomes. A growing body of empirical research has been relating cross-country differences in key economic outcomes such as productivity or output per capita to differences in policies and institutions that shape the business environment. Further, a branch of empirical research has attempted to shed light on the determinants of productivity at the firm-level and the evolution of the distribution of productivity across firms in an industry. In this paper, we exploit a rich source of data with harmonized statistics on firm level variation within industries for a number of countries. Our key empirical finding is that there is substantial variation in the within-industry covariance between size and productivity across countries. Drawing from the recent literature, we develop a model in which heterogeneous firms face adjustment frictions (overhead labor and quasi-fixed capital) and idiosyncratic distortions. We show that the model can readily be calibrated to match the observed cross-country patterns of the within-industry covariance between productivity and size, but find it more difficult to match observed cross-country variation in productivity dispersion within industries.

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1. **Introduction**

A vast theoretical and empirical literature has been devoted to identify the sources of the large and persistent differences in productivity across countries. A parallel literature has emerged over the past decade to explore the heterogeneity in productivity within industries observed in the firm-level datasets that have become available in a wide variety of countries (e.g. Bartelsman, Haltiwanger, and Scarpetta (2004)). Syverson (2009) presents an overview of the research into the sources of firm-level productivity heterogeneity within industries, ranging from firm-level decisions (e.g. managerial practice, innovative activity) to policy environment (e.g. competition, trade, resource flexibility).

A recent line of enquiry has been to connect the insights and the questions from these two literatures. That is, to explore the extent that cross country differences in outcomes like productivity are related to differences in the within industry productivity patterns across firms observed in a country. For example, recent papers explore the interplay between firm-level productivity heterogeneity, policy environment, and economic performance at the aggregate level. (see e.g. Restuccia and Rogerson (2008), Hsieh and Klenow, (2009) and Alfaro et. al. (2008)). In this emerging literature, an open question is what firm-level variation within a country is instructive for detecting the presence of misallocation distortions. Hsieh and Klenow (2009) argue, for example, that a higher dispersion of differences across firms within an industry in measured productivity reflects misallocation of resources.

Our paper continues this line of research with two primary differences from the recent literature. First, we argue that a more robust moment both empirically and theoretically for exploring the impact of misallocation distortions is the within industry covariance between size and productivity. Second, we extend models in the recent literature by permitting misallocation

distortions to not only distort the allocation amongst existing firms but also to permit the possibility that such distortions yield improper selection or churn of firms.²

The motivation for our approach is that the empirical evidence from firm-level data sources has shown that the widespread heterogeneity in firm-level performance is accompanied by substantial heterogeneity in the size of firms even within narrowly-defined industries. Moreover, consistent with core models of the size distribution of firms (e.g., Lucas (1978) and Melitz (2003)), there is evidence in the firm-level data that the distributions of productivity and size exhibit a positive correlation – that is to say, more productive firms tend to be larger than less productive ones. Our cross-country data suggest that there is considerable variation in the strength of the link between productivity and size across countries, between industries, and over time. The working hypothesis of this paper is that policy-induced misallocation distortions may be the source of the observed variation in this covariance across countries.

This misallocation hypothesis is not new (see, e.g., the discussion of these ideas in the literature in the handbook paper by Banerjee and Duflo (2003)) but the development of firm-level databases in a variety of countries now permits exploring this issue more directly. In this paper, we explore the misallocation hypothesis using different moments drawn from a harmonized firm-level database for the U.S. and a number of European countries, including transition economies of Eastern Europe. Our focus is to assess the extent to which distortions can account for the observed differences in the within-industry productivity dispersion, as discussed by Hsieh and Klenow, and for the observed differences in the covariance between productivity and size across countries. Further, we emphasize the importance of distortions on the selection of firms---*who produces?*---in additions to the allocation of resources across firms.

² Restuccia and Rogerson (2008) develop their model to permit misallocation distortions to impact churning and selection but do not explore this aspect of their model in their numerical analysis.

To quantify the within-industry covariance between size and productivity, we use an established empirical decomposition of the *level* of industry productivity as proposed by Olley and Pakes (hereafter OP, 1996). The OP decomposition splits an index of industry-level productivity, defined as the weighted average of firm-level (log-)productivity, into an *un-weighted firm-level average* and a *covariance term*. The covariance term is a summary measure of the *within-industry* cross sectional covariance between size and productivity. In our analysis, we find that the OP covariance term averages about 50 log points within U.S. manufacturing industries: in an accounting sense, this implies that the industry index of labor productivity in the average U.S. manufacturing industry is 50 percent higher than it would be if employment shares were randomly allocated within industries. However, the OP covariance 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, the covariance term increased substantially as the transition process evolved in these countries.

The use of the OP covariance term to explore the role of market distortions is, of course, not new. In their seminal contribution, Olley and Pakes found that the covariance term (using a decomposition of industry Total Factor Productivity, 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 covariance term in the transition economies following their market-oriented reforms could suggestively be interpreted as a quantitative measure of the success of these reforms, at least in terms of productivity performance.

One of the contributions of this paper is that we have a large set of countries and a variety of moments to use in confronting the model with the data. In particular, we focus on the within-industry standard deviation of labor productivity and total factor productivity and the within-industry covariance between labor productivity and employment shares for a range of countries. The individual moments, as well as the relationship between them, prove instructive in assessing the role of misallocation and this class of models. For example, a robust finding from our harmonized data (as well as in the related literature – see Syverson (2004a)) is that the within-industry dispersion of labor productivity is larger than the within-industry dispersion of multi-factor productivity.³ This finding is difficult to reconcile with many of the standard models in the literature insofar as they have specific features that do not allow for any dispersion in labor productivity. In particular, the production function is often assumed to be Cobb-Douglas or, more generally, has the property that the *average* product of labor is proportional to the *marginal* product of labor. Moreover, many models make assumptions so that profit-maximizing firms equate the marginal revenue product of labor to the market wage. These two assumptions together imply that there should be no dispersion in labor productivity within industries (in the absence of distortions) even if there is significant dispersion in physical TFP. Our model includes frictions -- even in the absence of misallocation distortions -- such as overhead labor and quasi-fixed capital that yield dispersion in labor productivity and can account for the observed dispersion in labor productivity being larger than in TFP. In accounting for these features, we are careful to distinguish between physical and revenue-based measures of productivity in the model and the data as has been emphasized in the recent literature (Foster, Haltiwanger and Krizan (2008) and Hsieh and Klenow (2009)).

³ Syverson (2004b) reports that, within narrowly defined industries, the difference in the U.S. between the 90th and the 10th 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.

Furthermore, our simple model allows comparing and contrasting the effect of distortions on different moments in the data. For example, Hsieh and Klenow (2009) present evidence that dispersion in revenue based measures of TFP are higher in China and India than in the United States. They use the quantitative variation in such measures of dispersion to back out the implied distortions that can account for these patterns. In our setting, we have similar measures of dispersion in revenue based TFP for 8 countries, but we also have the measures of the dispersion of revenue-based labor productivity as well as the covariance between firm size and revenue labor productivity for the same countries.

To preview our main results, we find that the model can be readily calibrated to match the cross-country within-industry patterns of the covariance of productivity and size, while it is more difficult to match the cross-country within-industry productivity dispersion patterns in the data. As will become clear, the reason is that the cross-country productivity dispersion patterns in the data and the model are less systematic than the cross-country covariance patterns.

The paper proceeds as follows. Section 2 describes the harmonized firm-level database used in our empirical analysis and presents some basic facts about the within-country productivity dispersion (TFP and labor productivity) as well as the empirical OP decompositions of productivity. In Section 3, we develop our model of allocative efficiency with idiosyncratic distortions in the selection and allocation process. Section 4 calibrates the model numerically to explore its implications in light of the empirical patterns discussed in Section 2. Section 5 reports the results from the numerical simulations of the impact of misallocation distortions on the key moments and explore the extent to which we can match the cross-country patterns of key moments observed in the data. Section 6 reviews our results relative to those presented in recent literature, while Section 7 presents our concluding remarks.

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

For the empirical analysis in this paper, we use key firm-level moments drawn from a harmonized firm-level database that covers five industrial economies and three transition economies of Eastern Europe.⁴ The database was constructed using firm-level data from business registers, social security and corporate tax rolls, and enterprise surveys.⁵ In the construction of the database, particular attention was devoted to harmonizing, to the extent possible, key concepts (e.g. 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 and the measures of outputs, inputs, deflators and productivity measures can be found in Bartelsman, Haltiwanger, and Scarpetta (2009) but we provide a brief overview here.

The firm-level data of the eight countries included in our analysis cover the manufacturing sector and include variables permitting consistent measurement of output, employment, materials and capital inputs. The measure of gross output is based on sales data at the firm-level deflated with an industry level deflator (2- or 3-digit industries). The measure of labor input is based on the number of employees, while the measure of capital is based on book values with further adjustments described in detail in Bartelsman, Haltiwanger and Scarpetta

⁴ The overall database covers as many as 24 countries (a downloadable version of the data can be found at http://econweb.umd.edu/~haltiwan/BHS_jobflows_productivity/). However, given the focus on within-industry dispersion of labor and multi-factor productivity and on the OP covariance term we restrict our attention in this paper to the U.S. and European (including transition) economies for which we have the required industry-level data. One of the countries that we include in the analysis (Germany) does not have the required within-industry multi-factor productivity measures but we include it nonetheless given its relevance in the cross-country comparison..

⁵ The firm-level database was assembled as part of long-term research projects sponsored by the OECD, the World Bank and Eurostat. The methodology for collecting the country/industry/time panel dataset built up from underlying micro-level datasets has been referred to as ‘distributed micro-data analysis’ (Bartelsman 2004). A detailed technical description of the dataset may be found in Bartelsman, Haltiwanger and Scarpetta (2009). Harmonized code for creating the indicators were distributed to experts with access to the relevant data in each country (typically a researcher with access to or a staff member of the national statistical agency).

(2009). The measure of materials is based on nominal materials expenditures deflated with an industry-level materials deflator. Total factor productivity calculations use expenditure shares for labor, capital and materials.⁶ Since all gross output and materials are deflated with industry-level deflators, the measures of real labor productivity (LPR) and real multi-factor productivity (TFPR) are revenue-based measures so they do not control for within-industry variation in firm-level prices.

There are a number of conceptual and measurement (e.g., index number) problems in comparing productivity across countries and, within each of them, across industries. We avoid some of these problems by focusing on within-industry measures of dispersion and covariance. Moreover, in order to facilitate cross-country comparisons and, in particular, to remove the possible influence of differences in the industry composition of the manufacturing sector in the cross-country comparisons, we construct country-level indexes by taking the weighted average of the within-industry measures using a common set of industry weights. For all of the data analysis in this paper, we use time-invariant U.S. industry gross output shares or labour shares as weights.

Three basic measures from this harmonized data are used in this paper. The within-industry standard deviation of log revenue labor productivity (LPR), the within-industry standard deviation of log revenue total factor productivity (TFPR), and a measure of within-industry covariance between size and productivity (OP). To compute the covariance measure we exploit the cross sectional decomposition of the following industry-level index of productivity developed by Olley and Pakes (1996). They note that an index of productivity for an industry, defined as the weighted average of firm-level productivity, can be decomposed as follows:

⁶ The measure of TFPR we use here is denoted as MFP in the Bartelsman, Haltiwanger and Scarpetta (2009) paper and dataset.

$$\Omega_t = \sum_i \theta_{it} \omega_{it} = \bar{\omega}_t + \sum_i (\theta_{it} - \bar{\theta}_t)(\omega_{it} - \bar{\omega}_t)$$

where Ω_t is the industry index, ω_{it} is firm-level productivity, θ_{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 industry index is comprised of two terms: the un-weighted average of firm-level productivity and a covariance term that reflects the extent to which firms with higher than average productivity have a higher than average market share. Olley and Pakes (1996) used this decomposition to show that, following the deregulation of the telecommunications markets in the U.S. in the early 1980s, the covariance term increased substantially in the telecommunications equipment industry.

It is the second term in this decomposition – the within-industry covariance term--that we use in our analysis. By construction, the covariance term is not affected by country or industry-specific effects; as such it is exempted from possible measurement error that impacts first moments at the country or country-industry level. For the empirical analysis in this paper, we use log labor productivity at the firm level as our measure of ω_{it} and the firm’s labor share in the industry as our measure of θ_{it} . We focus on the covariance measure using labor productivity since it is more readily available at the industry level for our sample of countries.⁷

Table 1 shows the three moments of interest for the sample of eight countries used in this analysis. Several observations are worth making. First, the within-industry dispersion of both revenue labor productivity and revenue total factor productivity is large in every country. Second, within countries, the within-industry dispersion of revenue labor productivity always exceeds the within-industry dispersion of revenue total factor productivity. Thus, the finding by

⁷ As will become clear, in the calibration analysis that follows we compute the moments in the model in the same fashion that we compute them in the data. That is, for example we compute revenue labor productivity and compute the OP covariance term using revenue labor productivity and employment weights.

Syverson (2004*b*) is pervasive across countries. Third, the covariance term is positive for almost all countries but exhibits systematic and notable cross-country patterns: in particular, the covariance term is the highest in the U.S. manufacturing, it is much lower on average in the Western European countries and even lower in the transition economies of Eastern Europe.⁸

It is also instructive to explore the within-country variation over time in these moments. These moments are available for a number of years spanning the period 1992-2001 for all countries, except France where data are available through 1995. We construct simple long differences for each moment by taking the difference between the average for the period 1996-2001 and the average for the period 1991-1995. Table 2 reports the within country changes of the moments computed in this fashion.

A number of observations emerge. First, the dispersion measures are relatively stable over time for the U.S., Western European and transition economies. Second, the covariance term increases substantially for the transition economies but only increases slightly for the U.S. and the Western European economies. This is consistent with the view that in Central and Eastern Europe the transition to a market-based system has over time allowed for a better allocation of resources; the U.S. had more stable market structures and economic institutions over this period and thus less marked changes in the covariance term.

Overall, the covariance term exhibits systematic cross-country variation in terms of both levels and changes. The within-industry dispersion measures are all large and relatively stable over time. In addition, there is a systematic pattern that the dispersion of labor exceeds the dispersion of total factor productivity in all countries. These are the key features of the firm-level data that we confront with the model analysis below.

⁸ A slight exception to this pattern is that Hungary and the U.K. have about the same covariance term. While productivity performance were rather weak in the U.K. in the 1990s (see e.g. Scarpetta (2003) it remains somewhat of a puzzle why also the OP covariance term was so weak in that period in the U.K.

3. A Simple Model of Idiosyncratic Distortions, Selection and Allocation

To guide our analysis of distortions and allocative efficiency we develop a simple model drawing heavily from Restuccia and Rogerson (2008) and Hsieh and Klenow (2009). In our model, heterogeneous production units are characterised by diminishing returns (as in Hopenhayn (1992) and Hopenhayn and Rogerson (1993)) and face *idiosyncratic* distortions (as in Restuccia and Rogerson (2008)). The model differs from the recent literature in a number of key dimensions. In particular, the model captures an important fact observed in the data in all countries: the dispersion in revenue labor productivity within industries exceeds the dispersion in revenue total factor productivity, even in economies with little or no distortions such as the U.S. To match this finding, we include two key features in the model: 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:⁹

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

where Y_{it} is output for firm i 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 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

⁹ We use a value-added production function in the theoretical model and in the calibration. This implies that both in the model and in the calibration, measures of real labor productivity are real value added per worker. Since we match to cross country moments in Table 1 that use real gross output per worker dispersion and covariance measures there is a potential for some mismatch. However, the moments from Table 1 are within-industry dispersion and covariance measures and the results in the literature show that real gross output per firm and real value added per firm are very highly correlated within the same industry (Foster, Haltiwanger and Krizan (2001)). In a related fashion, the within industry standard deviation of real gross output per worker shown in Table 1 for the U.S. is almost identical to the standard deviation of real value added per worker for the U.S. in Syverson (2004a).

decreasing returns to scale, possibly related to some unobserved fixed factor – such as managerial ability, as in Lucas (1978). The decreasing returns hypothesis is one of the factors that insure 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, in turns, yields 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:

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

where $\rho < 1$. 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 that the inverse demand for good i is given by:

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

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 nominal output, in each period given by:

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.

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

where τ_i is the firm-specific and time invariant distortion to revenue for firm i , κ_{it} is the firm-specific time varying distortion, 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.¹¹ The disturbances to revenue, τ_i and κ_{it} can be interpreted broadly to include any distortion that impacts the scale of a business. The underlying motivation is that distortions to market structure and institutions have an idiosyncratic component, which may arise *de jure* as some regulations may only apply to firms above a certain size, or alternatively *de facto* as a result of favoritism or arbitrary and capricious behaviour associated with problems of graft, corruption and rent seeking by the public administration or other entities. The inclusion of idiosyncratic components of distortion is consistent with evidence that certain regulations apply different to firms of different size,¹² as well as enterprise surveys (e.g. the World Bank Investment Climate Survey, ICA) that firms within a country face market and policy-driven obstacles for starting up or conducting business that exhibit a substantial idiosyncratic component.¹³

To make the model and analysis tractable, we assume a simple *ex ante* and *ex post* timing of information and decisions at any given period. Ex ante, before a new firm enters, we assume

¹¹ In an earlier version of this paper, we also considered an explicit “capital” disturbance that distorted the relative price of capital and labor. This distortion could also yield misallocation although we found that, in practice, it primarily impacts the mix of capital and labor. For purposes of brevity, we have excluded this from the analysis but note that it is of interest to consider other sources of distortion beyond those that affect the scale as considered in this paper.

¹² For example, regulations affecting the hiring and firing of workers only apply to firms above a certain threshold in a number of countries (see e.g. Venn, 2009).

¹³ In many developing and emerging economies, labour and other regulations are *de facto* enforced to a different degree across firms of different size, sectoral affiliation etc. (see e.g. Pierre and Scarpetta, 2004; World Bank, World Development Report, 2005; Aterido *et al.*, 2007).

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, $G(A, \tau)$. Once a firm learns their draws of A and τ their values remain constant. Each period the firm is subject to a further idiosyncratic productivity shock and an idiosyncratic distortion 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:

$$(3) \quad W(A_i, \tau_i) = E [\pi(A_i, \tau_i, \kappa_{it}, \varepsilon_{it})] / (1 - \chi)$$

where

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

In turn, the free entry condition is given by:

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

where c_e is the sunk entry cost.

New firms with a low productivity and/or a high scale distortion draw will immediately exit upon learning their draws if they cannot cover their operating costs. In what follows, we find that the subset of firms that survive upon learning their productivity and distortion draws is an important factor for assessing the effects of distortions. The surviving subset, $M(A, \tau)$, is comprised of the firms that enter based on their knowledge of the distribution $G(A, \tau)$, but that

did not exit owing to a non-positive present discounted value of operating profits, $W(A_i, \tau_i)$. Distortions thus 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). Even more importantly, the distortions and their potential correlation with idiosyncratic productivity, affect which firms survive.

Conditional on survival, the distribution $M(A, \tau)$, and the equilibrium input prices will determine optimal firm-level capital input. In addition, given the optimal amount of capital, the labor choice will depend upon the realization of the transitory shocks. It is useful to start backwards within a period considering optimal employment for a given capital stock which must satisfy:

$$(5) \quad \gamma \rho (1 - \tau_i - \kappa_{it}) (P_t \bar{Y}_t [A_i \varepsilon_{it} k_{it}^\alpha]^\rho (n_{it} - f)^{\rho-1}) = w_t$$

In turn the optimal capital stock must satisfy:

$$(6) \quad k_{it} = [\alpha A_i^\rho P_t E ((\bar{Y}_t (1 - \tau_i - \kappa_{it}) (\varepsilon_{it} (n_{it} - f)^\rho)^\rho) / R)^{1/(1-\alpha\rho)}$$

Output and profits for the operating firm are given by (1) and (2). Even though the firm is subject to a transitory productivity and distortion 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* transitory productivity and disturbance draws, $\varepsilon_{it}, \kappa_{it}$, by adjusting employment. The firm is of course deciding whether to produce and choosing its capital, conditional on the distribution of these transitory disturbances. 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 input.

To close the model we must describe labor supply and the behaviour of households and workers. 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 the equality of labor demand and aggregate labor supply.

$$W^e = 0, N_t^d = N_t^s$$

An aggregate resource constraint ensures that aggregate consumption plus resources spent on entry and depreciation will equal aggregate output in the stochastic steady state:¹⁴

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

where K_t is the aggregate of capital of ex-post operating firms, and E_t is the number of entrants.

The interest rate is pinned down by the production technology and utility maximization by the households. We assume a representative household that supplies labor inelastically and chooses consumption to maximize:

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

Subject to the budget constraint:

¹⁴ In steady state gross investment is only equal to replacement investment.

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

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.

4. Calibration of Benchmark “U.S.” Model

We calibrate the model in two steps. First, we choose some “benchmark” parameters based upon the key U.S. moments from Table 1. For the purpose of this first step “benchmark” calibration, we make the assumption that the U.S. is a non-distorted economy and choose key parameters to match U.S. moments under the assumption that the distortions in the model are zero.¹⁵ The objective then is to consider whether we can match the cross-country variation in Tables 1 and 2 using variation in the distribution of distortions only. That is, we assume that all countries face the same technology, the same distribution of technology shocks, the same curvature parameters of the profit function and then seek to account for the variation in Tables 1 and 2 across countries using variation in the distortion parameters alone.

¹⁵ The recent literature has focused on different moments to generate a U.S. benchmark. We provide some discussion of these alternatives in Section 6.

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 (2009) call TFPQ)) is given in the model by the product $A\mathcal{E}$ with the permanent component of physical productivity given by A . The measure of revenue TFP (what Foster et. al. (2008) and Hsieh and Klenow (2009) call TFPR) and the associated measure of revenue labor productivity (what we refer to as LPR) are also of interest. 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 $\log(\text{TFPQ})$, $\log(\text{TFPR})$ and $\log(\text{LPR})$.¹⁶

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 moment associated with this specific decomposition varies as the distortions vary. 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:¹⁷

¹⁶ In the discussion that follows in the text, when we refer to TFPQ, TFPR and LPR we typically omit the reference to logs for expositional convenience but in all cases log based measures are used.

¹⁷ We have conducted robustness analysis on each of these parameters and the findings in the paper are robust to reasonable variations in these parameters.

- $\gamma = 0.95$, (returns to scale – much of the evidence points towards close to constant returns to scale – see the discussion in Baily, Hulten and Campbell (1992), Syverson (2004a), Foster, Haltiwanger and Syverson (2008))
- $\alpha = 0.3$, (capital output elasticity) so the implied labor elasticity γ is 0.65 (these are close to standard choices for these parameters)
- $\lambda = .10$, 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 (2004) and Davis, Haltiwanger and Jarmin (2007))
- $r = .02$, 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 implies a markup of 25 percent.

The remaining parameters include the overhead labor parameter f , the entry cost c_e and the variances of the permanent and transitory productivity shocks. To pin these parameters down for the benchmark model, we use the information in Table 1 for the U.S. along with auxiliary information from the harmonized database on survival rates. Our model is not well suited to explore the dynamics of survival since the model does not allow for any uncertainty about type or other learning that are likely to influence the selection dynamics of entering cohorts of businesses. However, our model has a form of endogenous selection of young businesses as entrants pay the entry fee, learn their productivity and distortion draws and decide whether or not to produce. To approximate this process, we use information on the exit rates of young businesses in the U.S. In our harmonized data, about 55 percent of businesses survive after five

years in the U.S. This is about the same as can be found from other U.S. sources such as the Business Dynamic Statistics from the U.S. Census Bureau (see http://www.ces.census.gov/index.php/bds/bds_home). We match this moment in our calibration so that in the benchmark non-distorted economy 55 percent of the businesses that pay the sunk entry cost survive. We then seek to match the U.S. moments in Table 1. Not surprisingly, we have found the survival, dispersion and covariance moments are all closely connected. For example, setting a high overhead labor parameter yields lower survival rates as fewer firms can cover their fixed operating costs and leads to both lower dispersion of productivity measures and a lower covariance, as a larger fraction of the lower tail of the productivity distribution of firms is being cut-off.

In practice, we have found that we can match exactly the survival rate and one of the moments in Table 1 for the U.S. and approximately the other remaining moments in Table 1. The reason, as discussed in more detail below, is that the moments are nonlinear functions of key parameters. We have chosen for this analysis to match exactly the OP covariance term so that in our benchmark calibration we have a survival rate of 55 percent and an OP covariance term of 0.51 (the value in Table 1 for the U.S.). For the standard deviation of revenue total factor productivity (TFPR) the benchmark calibration has 0.43 compared to 0.38 for the U.S. in Table 1. For the standard deviation of revenue labor productivity the benchmark calibration has 0.68 compared to 0.58 for the U.S. in Table 1. While we do not obtain exact matches to all of the relevant U.S. data moments, they are reasonably close and the calibrated benchmark model has the property that the standard deviation of revenue labor productivity exceeds the standard deviation of revenue total factor productivity as observed in the data.¹⁸

¹⁸ We have also considered benchmark calibrations where we benchmark to the U.S. standard deviation of TFPR. The impact of distortions is quite similar both qualitatively and quantitatively to what we present

Some other properties of the benchmark model are worth noting since they are relevant for the analysis of distortions. In the calibrated model, we also compute the OP covariance term for revenue total factor productivity (in this case using revenue weights) and obtain an OP covariance term for TFPR of 0.41. In like fashion, we compute the OP covariance term using physical productivity in the model and obtain an OP covariance term of TFPQ of 0.96 (using physical output weights). Thus, the calibrated model has the property that more productive businesses are larger on a number of different dimensions. This is not surprising since the source of heterogeneity in the benchmark model is idiosyncratic productivity variation and more productive businesses employ more workers, use more capital and produce more output.

Two other properties of the benchmark model are worth noting. First, in matching the moments, we obtain a share of overall labor that is accounted for by overhead labor of 0.17. This is reasonably high. To put this in perspective, we note that in the U.S. manufacturing, non-production workers account for roughly 0.30 of total employment. Classifying all non-production workers as overhead labor is probably too strong an assumption, but our 0.17 is well within this upper bound estimate and seems not unreasonably high.

Another instructive statistic from the calibrated model is the share of overall output accounted for by entry costs. Recall that output is used for consumption, capital accumulation (replacing depreciated capital in equilibrium) and entry costs. In the non-distorted economy, we find that about 7 percent of output goes to entry costs. This reflects the costs incurred via the ongoing churning process with some businesses exiting on an ongoing pace and other businesses paying sunk entry costs to learn their draws and decide to produce. As will become clear, this

here. We focus on the benchmark calibrated to the OP covariance term in the U.S. since we can match exactly the OP covariance term patterns in Table 1 by permitting only the distribution of distortions to vary.

statistic is sensitive to the scale distortions and will be one of the factors that influence the relationship between distortions and consumption.

Before proceeding to the effects of the idiosyncratic distortions, it is worth highlighting the role that overhead labour plays in our exercise of matching the key moments in the U.S. data. Figure 1 shows the patterns for a number of key moments and outcomes as we change the overhead labor parameter f , but keeping all other parameters constant.¹⁹ The far right data point for each of the lines in Figure 1 is the benchmark calibration for the U.S. As the overhead costs are reduced relative to the benchmark, the OP covariance term is reduced, the standard deviation of LPR is reduced and the firm survival rate increases. It is clear from Figure 1 that overhead labor plays a critical role in matching a number of key features of the U.S. data. First, it is critical for matching the finding that there is greater dispersion of revenue labor productivity relative to revenue total factor productivity. Second, overhead labor is critical for matching the magnitude of the OP covariance term. Third, it is critical for capturing the high pace of exit of recent entrants. It is also worth noting (see more below on this point) that the presence of overhead labor is a distinguishing feature of our theoretical model and analysis compared with that in the recent literature.²⁰

Figure 1 also helps illustrate the difficulty of matching all of the U.S. moments simultaneously. The figure shows that as the overhead labor cost increases, the standard deviation of LPR and the covariance of size and productivity tend to rise but the standard deviation of TFPR does not change much. Note, however, that if we consider higher values of

¹⁹ Underlying figure 1 is variation in f . We present the results showing the implied variation in overhead costs (share of labor going to overhead) since this is more easily interpretable metric.

²⁰ In particular, Hsieh and Klenow (2008) do not consider fixed operating costs and have no endogenous firm selection. Restuccia and Rogerson (2008) permit fixed operating costs in the specification of their model, but set these costs equal to zero in their calibration. As it is apparent in Figure 3, it would not be possible for us to match the patterns in the U.S. data without including fixed operating costs in the form of overhead labor in our model.

overhead labor than those reported in Figure 1 that we find that eventually we observe the standard deviation of LPR and the covariance of size and productivity to decline with further increases in overhead labor.²¹ The reason for the latter is suggested by another key pattern in Figure 1 – that is, the share of entering firms that survive declines monotonically with overhead labor costs. As such, eventually such overhead labor costs become sufficiently high that so much of the distribution of firms is cut off by selection that these two moments begin to decline. The implication is that the standard deviation of LPR and the covariance tend to have an inverted u-shape with respect to overhead labor costs. These nonlinearities make matching all of the moments in Table 1 for the U.S. not feasible, at least in the range of the benchmark parameters that seem reasonable and are consistent with those found in the literature.

5. The Impact of Misallocation Distortions

We now turn to assess the potential role of misallocation distortions. Our objective is twofold. First, we seek to explore the implications of such misallocation distortions for key outcomes of the economy – both to understand the mechanisms through which misallocation distortions may be working but also to assess their impact on welfare-related variables such as consumption. Second, we explore whether the patterns of dispersion and covariance displayed in Tables 1 and 2 can be accounted for and understood in terms of differences in the distribution of misallocation distortions across countries.

We proceed as follows. First, we present results that show how misallocation distortions impact key moments and outcomes. This analysis is instructive to shed light on how misallocation distortions work in this class of models, in general and in our specific version of

²¹ Results on considering higher values of overhead labor available upon request.

the model calibrated as described above. Second, we explore the extent to which we can match the cross-country patterns of the key moments in Tables 1 and 2.

We begin with a relatively simple version of misallocation distortions, that is to say, permanent misallocation distortions that are uncorrelated with any fundamentals. Figure 2 shows the results of increasing these misallocation distortions on different moments. The distortions increase from left to right, starting from the non-distorted (U.S. benchmark) case. We find that an increase in the dispersion of distortions yields an increase in the standard deviation of TFPR, a modest effect on the standard deviation of LPR, a decrease in the OP covariance terms for both LPR and TFPR, a decrease in the fraction of surviving firms with an accompanying increase in the cost of entry as a share of output, an increase in the capital-labor ratio and a decline in consumption. Both the capital-labor ratio and consumption are indices relative to the non-distorted economy so an index above (below) one indicates the variable has increased (decreased) relative to the non-distorted economy.²²

It is clear from Figure 2 that increasing the dispersion of the misallocation distortions has non-trivial effects on a number of indicators. One of them is the effect on the selection margin. As the “noise” from distortions is added, the churning of businesses that pay the sunk cost is increased and this has significant effects for example on consumption. In turns, the strong sensitivity of the selection margin implies that while the dispersion in TFPR rises with the dispersion in distortions, as expected, the quantitative increase is relatively small. In like fashion, the quantitative decline in the OP covariance terms is relatively small. The reason for these

²² For consumption, the log of aggregate consumption is computed and then converted to index form. For the capital-labor ratio, the log of the aggregate capital-labor ratio is computed and then converted into index form. The use of indices here are more interpretable given that level (even log level) units in the calibration are not meaningful. The remaining moments are all unit free.

outcomes is that the selection effect truncates the lower-end of the distribution of firms, which mitigates the impact on the other key moments.

A much stronger effects of distortions on the economy can be obtained by allowing their distribution to be positively correlated with the idiosyncratic productivity draw.²³ This positive correlation case could be interpreted as a form of progressive distortions, wherein firms that would otherwise be highly profitable and large given their high productivity are effectively taxed or induced to stay small. This hypothesis is consistent with empirical evidence (see e.g. the World Bank Investment Climate Survey, Aterido *et al.* 2007) that when regulations are very strict and enforcement more pronounced among large businesses and/or corruption and rent seeking loom large, it may be better to “fly beneath the radar screen”. Likewise, there is evidence, as best exemplified by the experience of the centrally-planned economies, that in countries characterised by widespread market- and policy-induced distortions, the largest businesses are not necessarily the most productive but rather those that receive preferential treatment.

Figure 3 shows the relationship between key moments and distortion dispersions when we allow the idiosyncratic productivity and the idiosyncratic distortion to be positively correlated. We set the positive correlation very high (about 0.95) and vary the dispersion of the distortions for this high degree of correlation.²⁴ We observe similar qualitative patterns to those in Figure 2 but the quantitative variation is much greater for specific moments. In particular, we

²³ Restuccia and Rogerson (2008) also consider correlated distortions and obtain broadly similar implications that correlated distortions have more of a quantitative effect. In their exercise, they calibrate the benchmark model (non-distorted) to the U.S. size distribution and then consider the impact of misallocation distortions. They do not seek to account for cross country differences in observed moments.

²⁴ For this case, we consider both permanent and transitory distortions. We have found that including both is important to match the patterns of the OP covariances across countries which is not surprising given the presence of both permanent and transitory productivity shocks.

find that increasing the dispersion of distortions yields an increase in TFPR dispersion, an initial decline and then an increase in LPR dispersion, substantial reductions in the OP covariance terms for TFPR and LPR, a decline in survival with an accompanying increase in the entry cost as a share of aggregate output, a decline in the consumption index and an increase in the capital-labor ratio index.

What lessons can 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 characterised by sizeable scale distortions have distorted size-productivity relationships, as measured by the OP covariance terms for both LPR and TFPR. Second, we find that, other than the size-productivity relationship, many other margins are affected, including the productivity dispersion, the selection margin and capital-labor ratio. Third, increases in the dispersion of distortions across firms reduce consumption. Fourth, the impact of the increase in the dispersion of distortions on the OP covariance terms and on productivity dispersion is much greater if the distortions are positively correlated with productivity. This makes intuitive sense as distortions in this case have greater bite as they are not just noise but actively induce the most productive firms to be smaller and the least productive firms to survive and be larger than would have been the case in a distortion-free environment.

We now turn to the second objective of our analysis where we try to match the observed cross-country differences in our key moments shown in Tables 1 and 2 by using differences in misallocation distortions alone. Figures 2 and 3 already suggest that it will not be feasible to match all of the patterns shown in Tables 1 and 2. It is clear from Figures 2 and 3 that matching the OP covariance term patterns is potentially feasible since there is strong monotonic relationship between increasing distortions and reducing the size-productivity relationship and

Tables 1 and 2 show systematic patterns in the OP covariance terms. However, Figures 2 and 3 also show that increasing distortion dispersion systematically yields some increase in the dispersion of TFPR but they do not show systematic patterns for the dispersion of LPR. Thus, matching these patterns with the distribution of distortions alone is not feasible.

Given this obvious challenge, we think it is instructive to show the patterns consistent with exactly matching the OP covariance terms in Table 1. Table 3 shows the model and data moments in this case along with the implied model implications for consumption. As is apparent, the different distributions of distortions are chosen to match exactly the cross-country variation in the OP covariance terms for LPR. The implied cross-country variation in the standard deviation for LPR in the model at best only roughly matches the patterns in the data. That is, in our database, the Western European economies tend to have about the same LPR dispersion, and the model yields roughly similar patterns. However, the model does not come close to matching the very high standard deviation of LPR in the transition economies. The model is also less effective in accounting for the cross-country patterns in the standard deviation of TFPR.²⁵

Taken at face value, the model yields interesting implications for the consumption patterns across countries. The general pattern is that the implied consumption index for most Western European countries is about 0.95 of that in the U.S. while the transition economies have an implied consumption index of 0.90 or lower. An exception to this pattern is the U.K. which has an implied consumption index close to 0.90 associated with its very low measured OP covariance term for LPR.

²⁵ We have found that it is possible to generate dispersion in TFPR that is smaller than the non-distorted economy by permitting a negative correlation between the idiosyncratic productivity and the distortion. However, even here we have not been able to match the full range of dispersion of TFPR in Table 1. Moreover, the patterns for the OP covariance terms as we seek to match these patterns don't come close to matching those for Table 1.

The calibrated model is also capable of capturing the changes in covariance terms in Table 2 for the transition economies. Using Figure 3 and Table 3 together, an increase in the covariance term from around 0 to 0.20 is associated with an increase in the consumption index of about 0.05 to 0.10. So again taken at face value, our results suggest that the improved size-productivity relationship in the transition economies can be associated with a substantial increase in consumption as a result of an improved allocative efficiency.

Given that we are not able to match all of the patterns in Tables 1 and 2, how should we think about these results? We have several thoughts. First, the difficulty of matching the productivity dispersion patterns may reflect the fact that dispersion in productivity measures is less robust to measurement error than other moments. In that regard, we find our evidence in Table 2 instructive since it shows that for the transition economies the OP covariance terms increase substantially but there is little evidence of changes in the productivity dispersion. Given that changes over time cancel out any country-specific measurement error in second moments, we think that the changes are more robust measures in this context. But the lack of a systematic pattern in the changes in productivity dispersion is suggestive that other factors other than misallocation distortions are likely to be required to account for the cross-country time series patterns observed in the data.

What other factors might account for the observed patterns for the dispersion in TFPR? We leave formal exploration of this question for future work but note that it is well known in the empirical productivity dynamics literature that many factors impact the dispersion of productivity. For one, productivity dispersion is much greater for younger businesses (see, e.g., Haltiwanger, Jarmin and Schank (2003)). As such, the patterns may reflect differences in the dynamism of young businesses across countries. Second, market structure and competition

impact the dispersion of productivity (see, e.g., Syverson (2004b)). Variation in the latter across countries may reflect a form of misallocation distortions but likely not be well modelled or captured by permitting a distribution of idiosyncratic distortions.

Moreover, there are many additional margins that may be impacted by some form of misallocation distortion that are not well captured in this model. From the empirical firm dynamics literature, we have learned that the first decade or so of the life of a firm has very rich dynamics. In the U.S., we observe that for each entering cohort there is a rich “up or out” dynamic (see, e.g., Haltiwanger, Jarmin and Miranda (2009) and Davis, *et al.* (2008)) with most young businesses exiting but conditional on survival young businesses growing faster than their more mature counterparts. Moreover, the related evidence (see, e.g., Foster, Haltiwanger and Krizan (2001, 2006)) is that the surviving young businesses have more rapid productivity growth than their more mature counterparts. One hypothesis is that what differs across countries is the nature of these post-entry dynamics (see., e.g., Bartelsman, Scarpetta and Schivardi (2004)). Exploring this margin is beyond the scope of this paper but highlights that the cross sectional moments that we emphasize in Tables 1 and 2 while interesting and instructive are unlikely to be the whole story.

At the end of the day, our view is that using this class of models to assess the potential effects of misallocation distortions is instructive for helping us understand some of the dimensions of the productivity distributions observed within and between countries. In particular, we think these models are well suited to exploring the size-productivity relationship within industries that we have found exhibit systematic patterns across countries and over time in the transition economies. However, the inability of these models to capture other features of the

cross-country evidence makes clear that refinements and/or alternative approaches are also needed.

6. Discussion of Results Relative to the Recent Literature

How do our results compare to those obtained using similar models in the recent literature? We have already recalled some of their key features, but it is useful to briefly revisit them here. Restuccia and Rogerson (2008) provide the core theoretical development that much of the recent literature has subsequently used. They calibrate a non-distorted version of their model to the U.S. size distribution and then explore the impact of misallocation distortions on outcomes like aggregate output and productivity. Hsieh and Klenow (2009) calibrate their model to match the measured distributions of TFPR in the U.S., China and India. Since their model has the property that TFPR dispersion would be zero in the absence of distortions, their approach is to assess the role of relative differences in the distribution of misallocation distortions across the three countries analysed.. Alfaro *et. al.* (2009) calibrate their model using differences in the relative size distribution of firms between the U.S. and other countries.

All of these recent papers share some common features with our analysis. In particular, they all consider heterogeneous production units – either in terms of the size distribution of activity or the dispersion in productivity and include idiosyncratic distortions that tend to have adverse impacts on key aggregate outcomes, such as output, consumption and productivity.

Within this framework, our contribution relative to this recent literature is multi-fold. First, we are the first to consider the size-productivity relationship in this context. We regard this relationship as critical to the canonical models of the size distribution of activity that all of these recent papers build upon. That is, in the absence of distortions, these models have the property

that the largest firms are the most productive ones. We think it is intuitive to think that misallocation distortions will have a non-trivial impact on the size-productivity relationship. We present novel empirical evidence on the size-productivity relationship using a sample of countries and explore the implications in the context of these models. Second, we focus on the empirical finding from our analysis (consistent with results obtained in the recent empirical literature) that labor productivity dispersion is larger than total factor productivity dispersion. We regard this basic feature of the firm-level data important since it highlights possible frictions that need to be taken into account even in the absence of misallocation distortions. Third, and in a closely related manner, we consider the role of misallocation distortions where there is a non-trivial role for endogenous selection. None of the recent papers we have just discussed calibrate their models permitting endogenous selection. In our setting, the role of overhead labor plays a critical role in matching key patterns in the non-distorted benchmark and also, in turn, serves as a key factor in permitting endogenous selection. Lastly, because we focus on multiple moments from multiple countries, our paper highlights the impact of misallocation distortions on different margins. As such, we find that it is difficult to match the combined multiple moment with the evidence from multiple countries. In this respect, our analysis serves as a source of caution about this class of models. That is, it is apparent from our findings that only permitting the distribution of misallocation distortions across countries is not sufficient to match a number of key patterns in the data and the model.

7. Concluding Remarks

In this paper, we provide empirical evidence that the within-industry distributions of productivity and size are closely related to each other and that this 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, although there are large differences even within this group of countries, and becomes stronger for transition economies as they progress in the transition to a market economy.

We confront these interesting patterns in the data with a model that seeks to account for variation in outcomes due to misallocation distortions. Our simple model with heterogeneous firms facing frictions (overhead labor quasi-fixed capital) and idiosyncratic productivity shocks and distortions provides a reasonable match to key patterns in the U.S. indicators of productivity and size built up from firm-level data. In particular, the model captures high dispersion in revenue based measures of total factor and labor productivity. Second, it captures the finding that dispersion in labor productivity dispersion is greater than dispersion in total factor productivity. Third, it captures the large positive covariance between size and productivity in the data. Finally, it captures the finding that, for any entering cohort, a large fraction of firms exit very quickly.

Using this model, we seek to match the cross-country variation in a number of these key moments using differences in the distribution of misallocation distortions alone. We are successful in matching one of the key patterns in the cross country evidence. That is, we find that the size-productivity relationship is much stronger in the U.S. than in Western Europe and, in turn, it is stronger in Western Europe than in the transition economies of Eastern Europe. Moreover, the transition economies exhibited large increases in the size-productivity covariance over the 1990s while the U.S. and Western Europe did not. In matching these patterns, our

calibrated model implies relatively large difference in consumption due to these misallocation distortions.

While we are quite successful in matching the size-productivity covariance patterns, we are less successful matching other patterns in the data. In particular, the theoretical model implies that dispersion in revenue based measures of total factor productivity should monotonically increase with an increase in the dispersion of idiosyncratic misallocation distortions to businesses. While this pattern makes sense theoretically, there are not systematic patterns in the measures of revenue based measures of total factor productivity in the data. In the discussion of these results, we note that it may be that this moment is less robust to measurement error. However, it is equally likely that the model is not capturing the various different factors that influence the dispersion of productivity. Put differently, it may be asking too much to account for productivity dispersion patterns across countries in the context of these steady state models of misallocation distortions.

We think our analysis helps shedding further light on the potentials of this class of models of misallocation to track key productivity moments observed in the data. While we believe these models with idiosyncratic distortions offer rich new insights they are quite simple relative to the theoretical and empirical models on firm behavior in the literature. For one, they 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. A more refined or different approach will be needed to capture the potential distortions to these multiple margins.

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Table 1: Within Industry Productivity Dispersion and OP Covariance Term

(weighted averages of industry-level data, U.S. Industry Weights)

	STD in Revenue Labor Productivity	STD in Revenue Total Factor Productivity	OP covariance term
United States	0.58	0.38	0.51
United Kingdom	0.57	0.41	0.16
Germany	0.72	NA	0.28
France	0.53	0.22	0.24
Netherlands	0.56	0.15	0.30
Hungary	1.03	0.91	0.18
Romania	1.05	0.56	-0.03
Slovenia	0.80	0.22	0.05

Notes: Averages over 1992-2001 data. Industry-level firm based TFP measures not available for Germany.

Table 2: Changes in Productivity Dispersion and OP Covariance Term

(weighted averages of industry-level data, U.S. Industry Weights)

	STD in Revenue Labor Productivity	STD in Revenue Total Factor Productivity	OP covariance term
United States	0.02	0.00	0.09
United Kingdom	0.04	0.03	0.06
Germany	0.06	NA	0.15
France	NA	NA	NA
Netherlands	0.01	0.00	0.11
Hungary	-0.03	-0.03	0.21
Romania	0.03	-0.03	0.25
Slovenia	-0.06	-0.02	0.16

Note: Change is difference in moment between average value in 1996-2001 and the average value in 1992-2005. Data for France only available from 1992-1995.

Table 3. Key data moments and model moments when the model is calibrated to match the OP LPR covariance

	COV LPR		STD LPR		STD TFP		Consumption
	Data	Model	Data	Model	Data	Model	index Model
United States	0.51	0.51	0.58	0.68	0.38	0.43	1.00
United Kingdom	0.16	0.16	0.57	0.58	0.41	0.61	0.91
Germany	0.28	0.28	0.72	0.55	na	0.57	0.95
France	0.24	0.24	0.53	0.54	0.22	0.58	0.94
Netherlands	0.30	0.30	0.56	0.55	0.15	0.56	0.95
Hungary	0.18	0.18	1.03	0.57	0.91	0.60	0.91
Romania	-0.03	-0.03	1.05	0.63	0.56	0.62	0.87
Slovenia	0.05	0.05	0.80	0.61	0.22	0.62	0.87

Figure 1. The impact of overhead costs on key moments

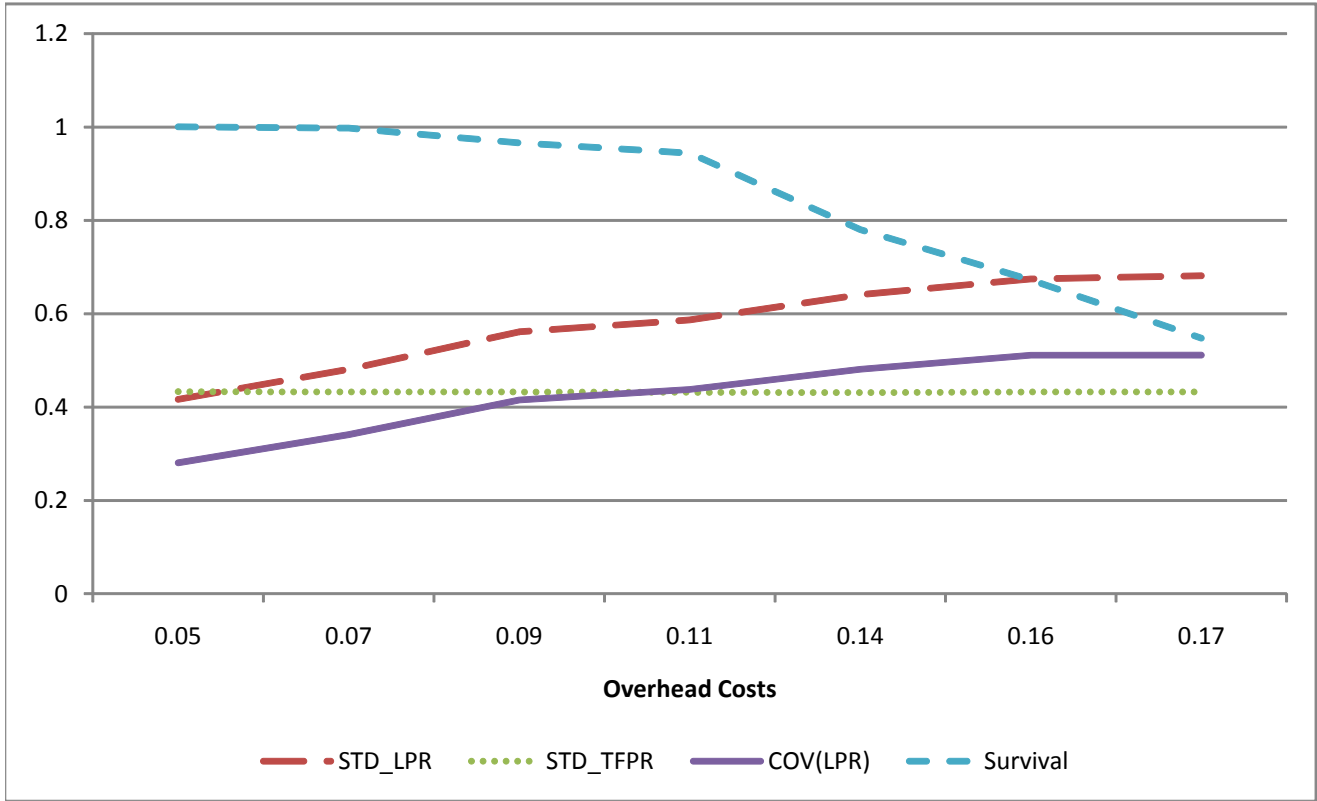


Figure 2: The Relationship Between Key Moments and Outcomes with Distortion Dispersion (Uncorrelated Case)

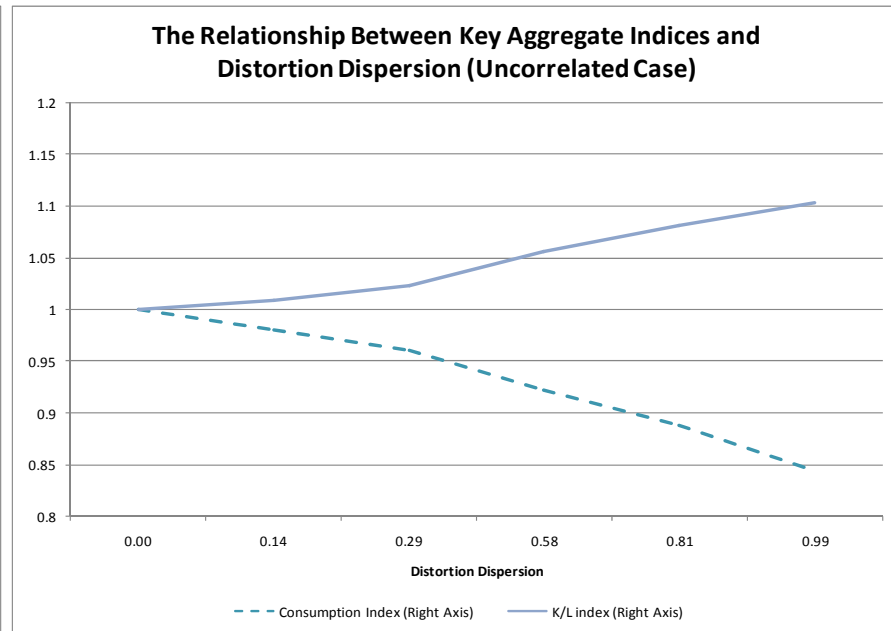
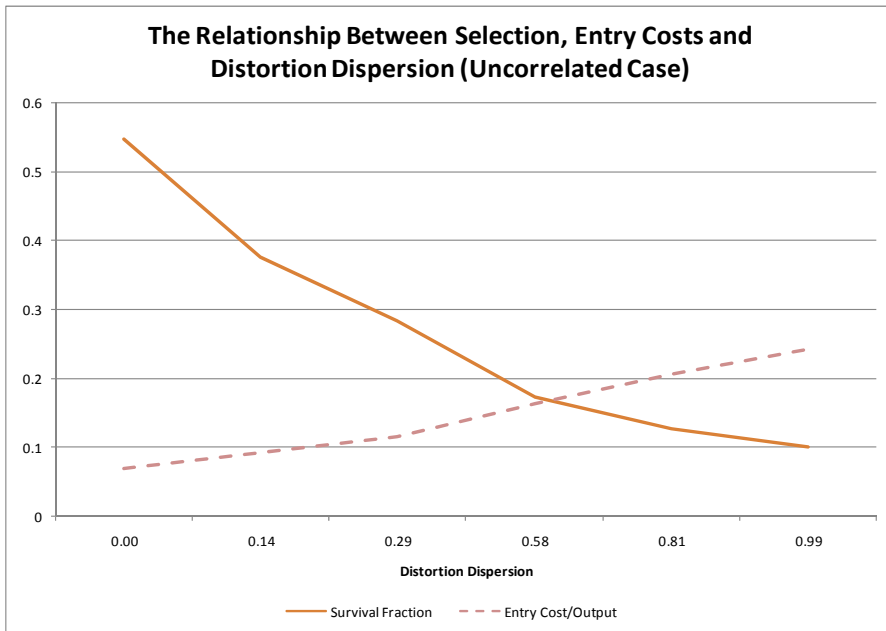
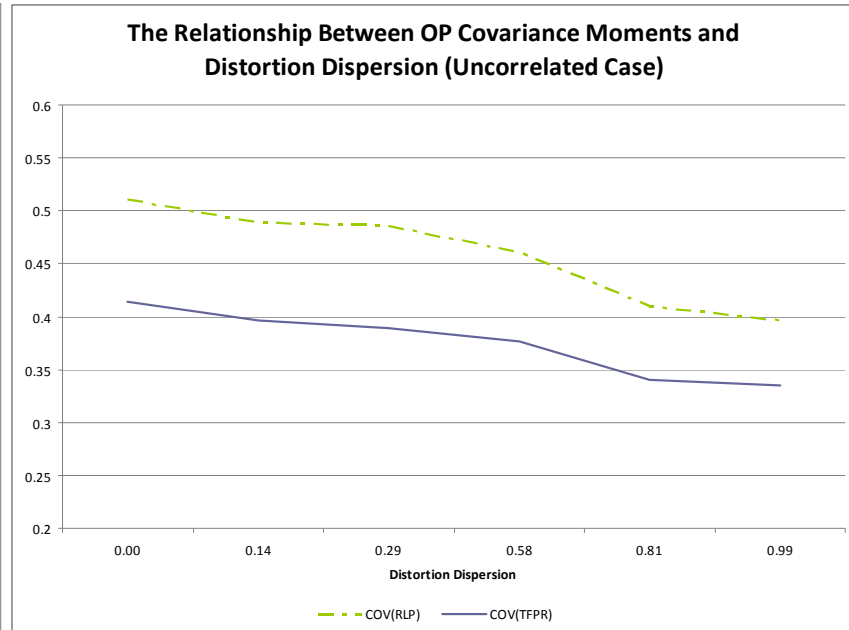
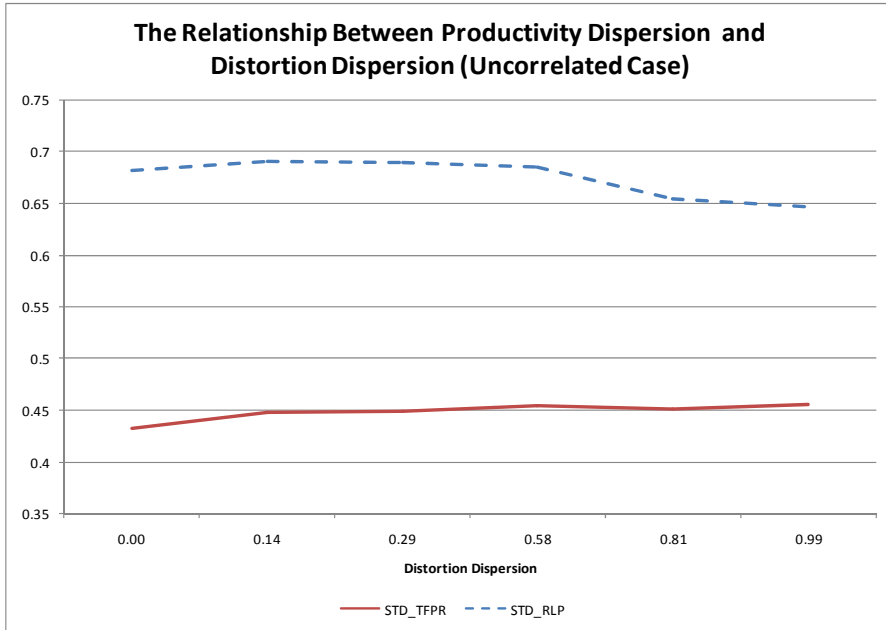


Figure 3: The Relationship Between Key Moments and Outcomes with Distortion Dispersion (Positive Correlation Case)

