ONLINE APPENDIX

CROSS-COUNTRY DIFFERENCES IN PRODUCTIVITY: THE ROLE OF ALLOCATION AND SELECTION

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This appendix presents a detailed sensitivity analysis to assess the robustness of the empirical results and model simulations presented in the main text. The appendix is organized as follows: Section I presents an alternative version of Tables 1 and 2 in the paper in which we present the manufacturing averages of the level and changes of the three key moments – STD(LPR), STD(TFPR) and OP – using country-average weights instead of US weights to aggregate industry-level indicators. Section II provides a detailed discussion on how we have related the data to model moments. Section III presents model simulations using alternative moments capturing the covariance between size and productivity. In Section IV, we further elaborate on the robustness analysis presented in Section V of the paper. In Section VI, we provide discussion of the relationship between aggregate consumption, output and aggregate indices of productivity in our framework.

I. Alternative Weights for the Construction of the Key Moments

Tables 1.A and 2.A present the estimated level and changes, respectively, of the three key moments used in our empirical analysis, namely: the within-industry standard deviation of log-revenue labor productivity, STD(LPR); the within-industry standard deviation of log-revenue total factor productivity, STD(TFPR); and the within-industry covariance between size and labor productivity, OP. The indicators presented in these tables represent manufacturing

TABLE 1. A - WITHIN-INDUSTRY PRODUCTIVITY DISPERSION AND OP COVARIANCE TERM

(WEIGHTED AVERAGES OF INDUSTRY-LEVEL DATA, CROSS-COUNTRY AVG. WEIGHTS)

	STD in Revenue Labor Productivity	STD in Revenue Total Factor Productivity	OP Covariance Term
United States	0.58	0.38	0.49
United Kingdom	0.60	0.43	0.15
Germany	0.70	NA	0.28
France	0.52	0.22	0.23
Netherlands	0.56	0.15	0.30
Hungary	1.03	0.90	0.19
Romania	1.05	0.52	0.05
Slovenia	0.80	0.22	0.05

Notes : Averages over 1993-2001 data. Industry-level firm based TFP measures not available for Germany.

Source : Firm-level database; see Bartelsman, Haltiwanger, Scarpetta (2009).

TABLE 2. A - CHANGES IN PRODUCTIVITY DISPERSION AND OP COVARIANCE TERM

(WEIGHTED AVERAGES OF INDUSTRY-LEVEL DATA, CROSS-COUNTRY AVG. WEIGHTS)

	STD in Revenue Labor Productivity	STD in Revenue Total Factor Productivity	OP Covariance Term
United States	0.02	0.00	0.07
United Kingdom	0.03	0.03	0.06
Germany	0.06	NA	0.15
France	NA	NA	NA
Netherlands	0.01	-0.01	0.11
Hungary	-0.02	-0.03	0.19
Romania	0.03	-0.03	0.23
Slovenia	-0.06	-0.02	0.16

Notes : Change is difference in moments between the average value in 1997-2001 and the average value in 1993-1996. Data for France only available from 1992-1995 and for the United States for 1992 and 1997.

Source : Firm-level database; see Bartelsman, Haltiwanger, Scarpetta (2009).

averages obtained by aggregating two-digit industry-level indicators using country averages of industry-weights, instead of the US industry weights as in the original version of the Tables. In other words, the average moments presented in the tables are constructed from industry-level indicators using the average economic structure of the countries in the sample instead of the economic structure of the U.S.

Comparing these Appendix Tables with the original Tables in the main text reveals that the key moments are very robust to the use of alternative weights for aggregating industry-level indicators to the manufacturing level. Both the average levels and the estimated changes from the first to the second-half of the 1990s are very close to those presented in the original Tables. The greatest differences are in the order of 0.03 log points for the indicators in level and 0.02 for the first differences, mostly concentrated among the transition economies whose economic structure differs more significantly from that of the US. It should also be stressed that similar results are obtained using country-specific weights to aggregate industry-level moments.

II. Measurement Issues in Relating Data to Model Moments

In this section, we discuss issues in comparing the calibration to the data moments in Tables 1 and 2. One issue is that 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. Because information on expenditures on intermediate inputs is less comprehensive in the firm-level data for some transition economies, we try to match the cross-country moments of Table 1 that are computed using real gross output per worker instead of value added. While there is a potential for some mismatch, we argue that it does not matter much in practice. 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)). For example, the within industry standard deviation of real gross output per worker shown in Table 1 for the U.S. (0.58) is almost identical to the standard deviation of real value added per worker that we calculated from the underlying data in an identical manner (0.60), and this is quite similar to dispersion in value added per worker for the U.S. calculated by Syverson (2004a). We also find the within-industry correlation between firm-level real gross output per worker and real value added per worker to be 0.82 in the U.S. Further, for about 3600 of the 5200 country/industry/time observations in the distributed micro analysis database of moments (predominately industrialized countries), we can compute productivity dispersion for both gross output and value added per worker. The correlation between the two measures for this sub-sample is 0.82.

III. Using Alternative Weights in the Covariance

As we discuss in the main text, the most robust prediction of models with heterogeneity in TFPQ and curvature in the profit function (from decreasing returns or downward sloping demand curves) is that high TFPQ firms should have high physical output. This prediction holds with minimal restrictions on the structure of demand. At the individual firm level, an increase in TFPQ will lower marginal costs and if the firm faces a downward sloping demand curve the effect will be larger. It will also be likewise generally true that high TFPQ firms will use the most inputs.

Distortions in this environment will decrease the correlation/covariance between TFPQ and physical output and TFPQ and inputs. These predictions regarding the correlation between productivity (measured as TFPQ) and size (measured as output or inputs) are illustrated in Figure 1.A for the uncorrelated distortion case and Figure 2.A for the correlated distortion case. Here for the input weighted case we use a composite input using factor elasticities as weights. It is apparent from these Figures that it does not matter qualitatively whether we focus on the OP covariance measure using output or input weights.

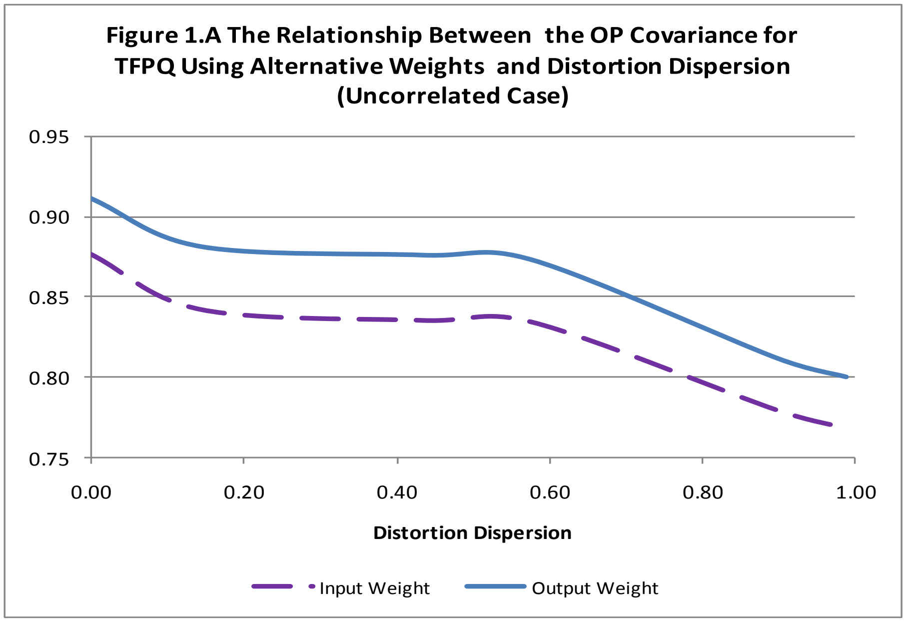

Figure 1.A The Relationship Between the OP Covariance for TFPQ Using Alternative Weights and Distortion Dispersion (Uncorrelated Case)

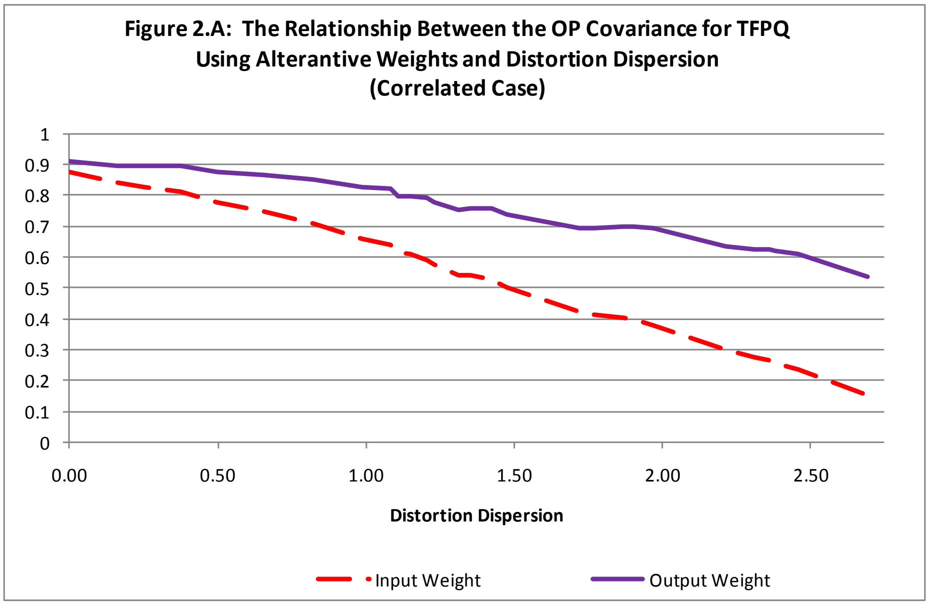

Figure 2.A: The Relationship Between the OP Covariance for TFPQ Using Alterantive Weights and Distortion Dispersion (Correlated Case)

As we have also noted in the main text, these predictions about size and productivity carry over to measures of size (as measured by employment) and productivity (as measured by labor productivity, LPR) or alternatively measures of size (as measured by a composite input) and productivity (as measured by revenue total factor productivity, TFPR). Such patterns are apparent in Figures 2 and 3 of the main text.

IV. Details on Robustness Exercises

In section V of the main text, we report the results of a number of robustness exercises. In this section, we provide more details about these exercises.

A. Lower Overhead labor

One of the key features of our theoretical model is the presence of overhead labor that significantly affects endogenous selection. As discussed in the main text, to assess the implications for our model simulations of a lower overhead labor, we set it very low so that all firms from the ex-ante productivity distribution produce in the absence of distortions. Results presented in the main text suggest that with very low overhead labor we cannot match the U.S. moments for labor productivity dispersion or selection. Hence, we benchmark the non-distorted economy to match the standard deviation of TFPR for the U.S...

Figure 4 in the main text presents the simulated results when we increase the dispersion of distortions (starting from zero). As in Figure 3 in the main text, we focus on the correlated case. Several interesting patterns emerge. First, as discussed in the paper, given the very low overhead labor, there is a substantial range over which increasing distortions has no impact on selection. It is only for large distortion dispersion that selection begins to bite. We intentionally did not set overhead costs to zero since we wanted to show that, if enough dispersion is introduced, this will push some firms to operate at such a small scale that they will not be able to cover their overhead labor costs, however small.

Second, it is clear that productivity dispersion both in terms of TFPR and LPR rises much more rapidly with distortion dispersion when selection is not playing a role (compare Figures 3 and 4 in the main text). The main message of this is that when overhead labor (fixed costs) and selection are at work, it becomes difficult to match a wide range of productivity dispersion using widening distortion dispersion.

Third, even with low overhead labor we find that the covariance between size and productivity declines with distortion dispersion. For TFPQ, we find that the covariance between size and productivity falls monotonically with distortion dispersion. This pattern is also present in Figure 3, where overhead labor and selection are relevant over the entire range. A robust implication of these models is that the covariance between size and productivity when using TFPQ is declining in distortion dispersion. This is intuitive and, in part, underlies our basis approach. Indeed, a core implication of models of firm heterogeneity in the absence of distortions is that higher TFPQ firms will be larger. Moreover, it makes sense that distortions to allocation will affect this covariance. Ideally, our data sources would include firm-level prices so that we could measure this covariance moment that is most robustly linked to distortions. However, measuring TFPQ directly is typically not feasible and we find the patterns for TFPR and LPR of interest as well. For TFPR, we tend to find a decreasing relationship between the covariance and distortion dispersion but this really kicks in once distortion dispersion gets sufficiently large.

For LPR, the covariance first increases over some range and then declines. The increasing portion reflects the fact that in the absence of distortions and overhead labor, there is relatively low LPR dispersion. The magnitude of the covariance depends on the magnitude of dispersion so over some range dispersion in LPR is so low that the covariance with LPR is also low. We don’t find it surprising that the patterns for LPR are less systematic in a low overhead labor environment with low distortion dispersion.

As is apparent from Figure 4 in the main text with low overhead labor we cannot match the observed pattern that LPR has greater dispersion than TFPR. Again, recall that this is a robust finding for all countries in Table 1 in the main text (and also a robust finding in Syverson (2004a)). With low overhead labor, this pattern can only be met with sufficiently large dispersion in idiosyncratic distortions. Once distortions are large enough so that this pattern is met, further increases in distortions yield patterns similar to those we report for our main results in the text.

B. Measurement Error

Measurement errors are a serious source of concerns for research using firm-level data. Measurement errors affect cross-country comparisons but are also likely to affect differently specific variables within a country dataset. For example, data on sales or revenue are likely to suffer from greater measurement errors than data on employment. At the same time, data on capital generally suffer from greater measurement error than both sales and employment. To shed some light on the potential impact of measurement errors on our model simulation results, we consider multiplicative measurement error in revenue (where the multiplicative factor is centered at one) and its impact on two key moments: the OP covariance term, using revenue labor productivity, and the standard deviation of TFPR. These findings are show in Figure 5 of the main text.

Figure 5 of the main text suggests that the OP covariance term is much less sensitive to revenue measurement error than is the standard deviation of TFPR. The reason is rather straightforward. Multiplicative measurement error in revenue yields increased dispersion in measured revenue relative to actual revenue, translating directly into the standard deviation of measured TFPR.

However, multiplicative measurement error in revenue that is classical does not change the measured covariance between LPR and employment. This follows from the property that the expectation of the product of uncorrelated variables is the product of the expectations. However, we note that multiplicative measurement error in employment has a substantial impact on both dispersion and the covariance. The strong impact on the covariance results from the fact that measurement error influences the denominator of LPR and the numerator of the employment weight yielding a negative contribution to the covariance.

C. Dispersion in Factor Elasticity for Labor

Our model relies on overhead labor to yield a higher dispersion in revenue labor productivity relative to TFPR, as observed in the data. In this subsection, we explore the use of heterogeneous factor elasticity of labor to try to reproduce this pattern between the dispersions in labor productivity and TFPR. The results of this exercise are shown in Figure 6 of the main text.

We use a parameterization of the model with low overhead labor, no distortions and no dispersion in factor elasticities. The leftmost point of all the series in Figure 6 of the main text corresponds to the leftmost point of all the series in Figure 4 of the main text. At this leftmost point, dispersion in TFPR matches that in the U.S. but is much larger than that of LPR. Moreover, the OP covariance term is relatively small and much smaller than that observed in Table 1 for the U.S. in the main text. It is precisely the poor performance of this model that motivated us to include overhead labor in the baseline of our model.

As we move to the right in Figure 6 of the main text, dispersion in the factor elasticity of labor increases (as does capital since in this experiment we keep the return to scale constant). Figure 6 of the main text shows that dispersion in LPR rises rapidly even for relatively modest dispersion in the factor elasticity of labor. But the Figure also suggests that the OP covariance falls rather than rises as the dispersion of the factor elasticity rises. The intuition for the latter is straightforward. Firms with high factor elasticity of labor have a lower capital/labor ratio for a given level of TFPQ which in turn yields a lower LPR.

It is apparent from Figure 6 of the main text that matching the key U.S. moments from dispersion in factor elasticities is not feasible. We also note that other features of the data work against this explanation. We find, for example, that persistence in labor shares in the U.S. over a five year horizon is only about 0.18. Presumably dispersion in factor elasticities would yield more persistence in labor shares at the plant level.

D. Negative Correlation Between Distortions and Productivity

As discussed in the main text, in order to match the observed cross-country patterns in the covariance between productivity and size, we had to impose a positive correlation between distortions and productivity. Uncorrelated distortions have a negative impact on the covariance between size and productivity but not enough to match the differences observed in the data. In this context, an interesting question is whether it would be possible to increase allocative efficiency and consumption in this class of models by introducing distortions that are negatively correlated with productivity (i.e. subsidizing most productive businesses). Model simulations suggest that allowing for a negative correlation between distortions and productivity can yield (at least modest) increases in the productivity/size covariance and consumption (starting from the U.S. benchmark, we have found we can increase the productivity/size covariance to 0.52 and the consumption index by less than one percent). However, as discussed in the paper, changing either the degree of dispersion or the negative correlation of distortions and productivity yields non-monotonic results, which is the result of the interaction of opposing forces. On the one hand, distortions by their very nature affect incentives. On the other hand, the non-distorted economy has its own distortions from market power such that businesses are not producing as much as they should given their productivity and the given level of market prices.

V. Aggregate Consumption, Output and Productivity

In the main text of the paper we focus our discussion of welfare on aggregate consumption as appropriate. But it is also of interest to consider the implications of distortions on other key aggregates such as output and productivity. Within our framework there is a tight relationship between aggregate output and aggregate consumption. Indeed, using the variation in the dispersion of distortions as depicted in Figure 3, we find that aggregate consumption and aggregate output have a correlation of 0.99. The implication is that an increase in the dispersion of distortions should, according to the model, be associated with decreases in aggregate output (per capita).

In considering aggregate measures of productivity, it is important to emphasize that there is no simple functional relationship relating aggregate output to aggregate inputs in our framework. Rather aggregate output emerges from a complex interaction of firm heterogeneity, frictions and distortions. This implies that interpreting standard measures of aggregate productivity in the context of this framework is an open question. Still, it is certainly possible to construct alternative aggregate measures of productivity in our framework and in turn it would be of interest (in future work) to relate such measures to their empirical analogues. For example, input-weighted measures of micro (firm-level) TFPQ and TFPR can be constructed within our framework. Using the variation of dispersion in distortions depicted in Figure 3, we find that the correlation between consumption and the aggregate TFPQ index constructed as the input-weighted firm-level TFPQ is 0.92. The analogous correlation between the aggregate TFPR index constructed as the input-weighted firm-level TFPR and consumption is

0.82. Thus, for both measures the message is that an increase in dispersion of distortions yields a decrease in these aggregate indices of productivity.

Yet another aggregate measure to consider is based on the relationship between aggregate output and aggregate inputs. As noted, there is no simple aggregate production function consistent with the theoretical framework. But consider a measure constructed as output per unit of resources used to generate that output. In our framework, inputs used to produce aggregate output include capital, labor and the resources used for entry. In our framework we measure the latter in units of output so for constructing this measure we simply subtract these resource costs from output. We weight capital and labor by their factor elasticities used for the firm-level production function. We find that the resulting aggregate index of output per unit of resources is highly correlated with the other measures discussed in this subsection. That is, using the variation used in Figure 3, this measure has a correlation with aggregate consumption of 0.98, a correlation with input-weighted TFPQ of 0.89 and a correlation with input-weighted TFPR of 0.79. Again, the message is that as dispersion of distortions increases this aggregate (somewhat ad hoc) productivity index decreases.