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Misallocation and Aggregate Productivity across Time and Space

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Abstract

Productivity is at the core of the large differences in income per capita across countries. What accounts for international productivity differences? I discuss cross-country differences in the allocation of inputs across heterogeneous production units—misallocation—as a potential factor in accounting for aggregate productivity. Policies and institutions generating misallocation are prevalent in poor and developing countries and may also be responsible for differences in the selection of operating producers and technology used, contributing substantially to aggregate productivity differences across countries.

JEL classification: O11, O14, O4.
Keywords: productivity, misallocation, selection, technology, regulation, trade, financial frictions, agriculture.

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1 Introduction

In this article I am concerned with the wide disparities in income per capita around the world. To illustrate the enormous disparities, Table 1 reports real GDP per capita across countries and over time for the average of countries in each decile of the income distribution, all expressed as a percentage of the United States in each year. There are large disparities in income per capita across countries at any point in time, from a factor difference between the richest and poorest deciles of 23-fold in 1960 to more than 50-fold in more recent years. Notice that even countries in the middle of the income distribution (fifth decile) have factor differences with respect to the top decile that range between 5.7 to 8.4-fold, so large disparities in income per capita are quite prevalent around the world.

Table 1: GDP per capita across Countries and Time

	Year						
Decile	1960	1970	1980	1990	2000	2010	2014
1	3.4	3.2	3.1	2.3	1.7	1.8	2.0
2	5.5	5.1	4.5	3.2	2.7	3.0	3.3
3	7.4	6.8	6.4	4.5	3.9	4.8	5.7
4	9.6	8.9	8.0	6.8	6.2	9.2	10.9
5	12.7	11.5	11.5	10.2	10.0	14.8	18.5
6	14.9	15.8	17.4	15.4	16.1	21.9	25.6
7	22.0	22.9	24.1	22.3	22.1	29.9	35.0
8	30.5	33.4	39.1	38.0	45.3	53.0	56.7
9	49.9	56.0	62.2	65.1	72.6	77.0	79.5
10	80.1	81.3	82.6	79.3	83.5	98.3	105.0
Ratio 10/1	23.4	25.4	27.1	34.0	49.5	53.6	51.3
Ratio 10/5	6.3	7.1	7.2	7.8	8.4	6.7	5.7

Notes: Real GDP per capita across countries from the Penn World Table v9.0 (expenditure based in PPP prices of 2011), see Feenstra et al. (2015). Average of GDP per capita in countries in each decile is reported relative to the United States in percent. Countries are ranked according to GDP per capita in each year. The sample comprises 101 countries with population greater than one million in 2005 which represents well the world distribution of income and population.

There are also substantial movements in relative incomes over time across countries. To appreciate the mobility of countries in the income distribution, Table 2 reports the evolution of relative GDP per capita for selected individual countries who are ranked according to relative income in 1960. The pattern that emerges is another well-known fact in economic development that growth successes and failures are unrelated to the initial level of development as we tend to observe country experiences of success and failure at any point of the income distribution. For instance, the success of Botswana—a very poor country in 1960 at 2.3 percent of the GDP per capita in the United States—managed to catch up to 29 percent of the United States in 2014, contrasts with failures to catch up in Ethiopia and Malawi at similar stages of development in 1960. Success experiences in Indonesia, China, India, Korea, and Singapore contrast with failure in Zimbabwe. Success and stagnation in Japan contrasts with only stagnation in Mexico. Even among the richest countries in 1960, growth paths differ substantially. We observe a strong catch up relative to the United States in Austria, less so in France, with stagnation in the United Kingdom and decline in New Zealand.

I focus in this article on the large disparities in income with some exploration of changes in income over time. In some respect, accounting for changes in income over time for individual countries represents a somewhat lower hurdle than the much larger differences in income across countries at a point in time. The article is organized as follows. First, I argue that the differences in income per capita across countries are mostly accounted for by differences in total factor productivity (TFP)—the rate at which a given set of aggregate factor inputs translates into aggregate output. So then the key question I focus on is: what accounts for productivity differences? Second, I describe a simple framework to discuss the potential channels though which the literature has tried to account for productivity differences across countries, channels that I broadly refer to as technology, selection, and misallocation. I use this simple framework to quantify the potential productivity effects of misallocation. Third, I discuss the evidence on misallocation and its likely causes with an eye to asking what specific policies and institutions are important in creating misallocation and their aggregate productivity impact. Finally, I discuss recent work studying the broader consequences of

Table 2: GDP per capita across Time for Individual Countries

Country	1960	1980	2000	2014
Botswana	2.3	7.5	21.5	29.1
Ethiopia	2.5	2.5	1.2	2.6
Malawi	4.7	4.3	2.1	1.9
Indonesia	5.3	7.1	9.0	19.8
China	5.6	5.7	9.5	24.6
India	5.9	4.0	4.4	10.5
Korea	6.2	18.3	50.5	68.2
Zimbabwe	11.3	10.0	6.1	3.1
Singapore	14.3	41.7	83.3	149.7
Japan	30.8	63.2	73.9	68.2
Mexico	32.0	38.1	25.4	31.1
Austria	53.4	62.9	77.8	92.7
France	59.4	75.4	68.3	76.5
United Kingdom	68.0	64.7	74.9	75.3
New Zealand	81.2	60.2	59.4	66.0

Notes: Real GDP per capita across countries from the Penn World Table v9.0 (expenditure based in PPP prices of 2011), see Feenstra et al. (2015). GDP per capita in each country is reported relative to the United States in percent. Countries are ranked according to GDP per capita in 1960.

misallocation on aggregate productivity via additional effects on selection and technology channels.

2 The Importance of Productivity

A broad consensus in the macro development literature is that, at the aggregate level, income differences across countries are mostly accounted for by TFP differences. This finding has been documented extensively in the literature, for instance Klenow and Rodriguez-Clare (1997), Prescott (1998), Hall and Jones (1999), Caselli (2005), and more recently Jones (2016). For instance, Jones (2016) performs a development accounting exercise that separates the contributions of physical capital intensity, human capital, and TFP in accounting for GDP per worker differences across countries. Note that there are modest differences in employment to population ratios across countries and these differences are not systematically related with income per capita. There are also modest differences in hours per worker across countries that, if anything, the evidence suggests is higher in poor relative to rich countries. As a result, accounting for income per capita differences across countries hinges on accounting for differences in labor productivity (income per worker or per labor hour). The overwhelming finding is that TFP accounts for most of the differences in GDP per worker across countries (e.g. Jones, 2016, Table 6, page 44).

Because in development accounting TFP is inferred as a residual from output and measured inputs, any mis-measured variation in inputs across countries would be attributed to TFP. As a result, there are two important elements in assessing the quantitative contribution of TFP on income differences. First, it is essential to measure aggregate physical capital in real terms, i.e. using common prices across countries, see for instance Restuccia and Urrutia (2001) and Hsieh and Klenow (2007). Whereas investment to output ratios in domestic prices tend to be fairly similar across countries—and hence similar implied capital to output ratios—real investment rates differ substantially across countries, a factor difference of 4 to 6-fold between rich and poor countries. Second, it is important to measure the quality of human capital. The key issue is that human capital is difficult to measure across countries as the most commonly available measures represent only proxies of the quantity of human capital such as the number of years of schooling of the relevant population. The main finding from the literature is that the importance of TFP in accounting for income differences remains even after accounting for differences in human capital. The modern approach to assess the quantitative importance of human capital suggests that while differences in the quantity and specially the quality of human capital across countries are important, these differences are driven by TFP, as emphasized for example in Erosa et al. (2010) and Manuelli and Seshadri (2014).[1]

At a more disaggregate level—at the broad sector level or at the firm level within sectors—there are also substantial differences in productivity across countries. This is particularly the case in agriculture where cross-country productivity differences are much larger than in the rest of the economy. Because poor countries allocate most of their labor to agriculture in contrast to rich countries, agriculture is essential in accounting for aggregate productivity differences between rich and poor countries.[2] More generally, Duarte and Restuccia (2010) show substantial differences across countries in sector productivity levels and growth that account for differences in economic structure and the time series patterns of structural change and aggregate outcomes.[3] While the role of sectoral productivity on structural transformation and aggregate outcomes is a subject of great importance, in what follows I abstract from the composition of the economy by discussing the work on productivity for the entire economy or for specific sectors of the economy without an explicit connection to structural change. Bloom and Van Reenen (2007) document substantial differences in firm-level productivity across countries that is partly accounted for by differences in management practices. Using management practice data across firms and countries, Bloom and Van Reenen (2007) show a strong association of management practices with firm-level productivity and survival

[1] See also Schoellman (2011).
[2] See for example Gollin et al. (2002) and Restuccia et al. (2008).
[3] See also the survey on structural transformation in Herrendorf et al. (2014).

rates; and substantial differences across countries.[4]

3 Accounting for TFP Differences

The key question I focus on is, what accounts for productivity differences across countries? A well-known possibility is that the most advanced technologies are slow to diffuse to low income countries. Another distinct but complementary possibility is that low income countries are less efficient in allocating their factors of production to the best uses, a situation that the literature has broadly referred to as misallocation. Casual observation suggests that both misallocation and slower technology adoption are relevant. In what follows, I focus on the evidence for misallocation, but a useful insight of recent work on misallocation, which I describe in Section 5, suggests that misallocation and technology differences may be driven in part by the same set of policies and institutions identified in the misallocation literature.

To facilitate exposition and characterize the specific concept of misallocation I focus on, I start by describing a simple framework of aggregate TFP in a country.[5] I consider a static setting where in each period a homogeneous good is produced by M potential production units that are heterogeneous in their total factor productivity. In each production unit, output y_i is produced according to

$$y_i = A_i \cdot h_i^{\gamma}, \qquad \gamma \in (0, 1),$$

where A_i reflects productivity of producer i, h_i is the labor input, and γ measures the extent of decreasing returns to scale at the production unit level.

Note that the production function is such that it would not be optimal to allocate all the labor to

[4]See also Bloom et al. (2010).

[5]The framework is mainly drawn from Restuccia and Rogerson (2017), which provides a much broader perspective on the literature on misallocation and productivity.

the most productive unit, generally implying a non-degenerate distribution of establishment sizes which we observe in reality. This is because there are decreasing returns to scale at the production unit level, implying that the marginal product of labor changes with the amount of labor allocated into a unit—the change in output varies with the amount of labor allocated to a unit. Decreasing returns to scale at the production unit level and labor as the sole input are not key in the discussion that follows. To appreciate this point, not that the input h can represent a composite input (capital, intermediate inputs, labor) so nothing in the economics I emphasize depends on h being just labor input. Similarly, at the aggregate level, and when the number of production units M is allowed to vary, the production function features constant returns to scale and, therefore, is consistent with a long tradition in macroeconomics. An alternative framework can be represented where instead of decreasing returns to scale at the production unit level, there are constant returns to scale but production units produce a variety of goods and those goods are valued by consumers according to preferences featuring a constant elasticity of substitution across varieties. As a result, in this case, the curvature is in preferences instead of the production side and none of the elements I emphasize critically hinge on these details of the production and demand structure.

In addition, I assume that each production unit is subject to a fixed cost of operation so it would not be optimal to operate all production units. Before describing the market arrangement, and as a benchmark for comparison, consider first the efficient allocation of resources—the allocation of labor across producers that maximizes aggregate output net of operation costs. Given aggregate resources, in this case, the aggregate amount of labor and the set of available production units, the efficient allocation involves selecting production units to operate that can cover the fixed cost and then to allocate inputs across operating units as a proportion of their productivity so more productive producers are allocated more inputs. In this setting, productivity is the only determinant of input allocation among operating producers, so establishments with the same productivity should operate at the same scale and more productive producers should be allocated more inputs.

I close the model by assuming competitive markets for outputs and inputs. I denote by w the real wage rate. The aggregate demand of labor by firms should equal the supply of labor which is assumed to be constant and normalized to 1. Notice that in this setting, a producer who is operating maximizes profits by choosing labor demand so that marginal revenue equates marginal cost, given by:

$$\gamma \frac{y_i}{h_i} = w,$$

which implies the following labor demand by producer i:

$$h_i = \left(\frac{\gamma A_i}{w} \right)^{1/(1-\gamma)}.$$

If all producers face the same cost of labor w and the same price for their output (which in this setting is normalized to 1), then their relative labor demand depends solely on their productivity so more productive producers operate larger establishments. It would be easy to show that this allocation achieves efficiency among operating producers, which in this case implies that in an efficient allocation, the average product of labor y_i/h_i is equalized across producers. To illustrate potential deviations from this allocation, consider for example two producers with different TFP (A_i) that operate the same amount of labor. In this framework, this situation can only be rationalized by producers facing different prices on labor or output (whether they are explicit or implicit). For instance, suppose producers face idiosyncratic output taxes so that they receive only a fraction $(1 - \tau_i)$ of output as revenue. Then the first order condition for profit maximization changes to,

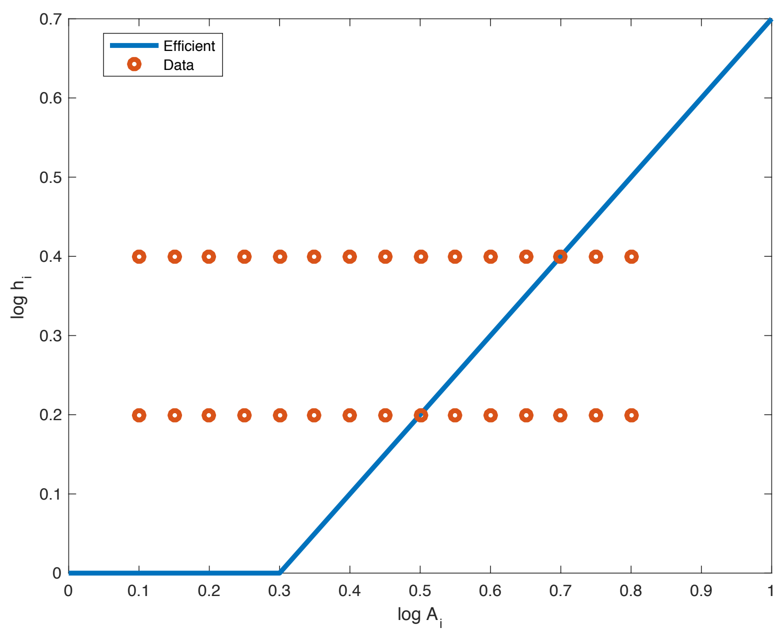
$$(1 - \tau_i)\gamma \frac{y_i}{h_i} = w.$$

Producers in this case equate the after tax value of the marginal output to the marginal cost and so the relative labor demand now depends on their productivity and output tax. Note that the average product of labor has common components across establishments as before but now also depends on $1/(1 - \tau_i)$. In the previous example, the two producers with different productivity can operate the same amount of labor if the tax difference exactly compensates the productivity difference. Of course, it could also be that some institution or policy restricts producers to operate the same amount of input so the optimality condition does not apply in practice. In this case, the output tax can be thought as a wedge that rationalizes the actual allocation with an equilibrium of this model, that is, the wedge would induce producers in a competitive market economy to choose the same allocation despite their productivity differences. As I discuss below, a challenge in studies of resource allocation is that many actual policies, frictions, and institutions in poor and developing countries generate distortions that are implicit and hence their impact cannot be easily measured with individual producer price data.

Broadly speaking, in this setting, there are three channels that can account for aggregate TFP differences across countries. First, it may be that countries have different producer-level TFPs—the set of A_i—broadly described as the technology channel. Second, it may be that even if producer-level TFPs are the same, countries may choose a different set of producers to operate, broadly described as the selection channel. Third, it may be that even if producer-level TFPs and the set of operating producers are the same, countries may choose a different allocation of resources across producers, broadly described as the misallocation channel. An important insight of current work on misallocation is that specific policies and institutions creating misallocation can have larger effects on aggregate TFP by also altering the technology and selection channels.

To illustrate the efficient allocation in this framework, Figure 1 presents a stylized efficient allocation, represented by the solid (blue) line, with establishment productivity A_i on the $x-$axis and the amount of operated labor on the $y-$axis. Since the relationship is highly non-linear, both axes are represented in logarithms. There is a threshold productivity below which establishment do not operate and above which more productive establishments operate larger units. Any allocation that deviates from this efficient allocation lowers aggregate output, and hence TFP since the aggregate amount of labor is fixed. Misallocation represents deviations from this benchmark efficient allocation. I emphasize that in this setting, lower aggregate output and TFP arises even if more resources are allocated to the more productive units, as this situation is a deviation from the efficient operational scale of production units.

Figure 1: Stylized Efficient Allocation and Misallocation



Notes: The blue line represents an stylized efficient allocation of labor across a set of producers that differ in total factor productivity A_i. The red circles represent hypothetical data on producers TFP and labor input.

I also illustrate in Figure 1 a stylized situation of misallocation by including hypothetical data of establishments represented by the circles (red). In the hypothetical data, there are two production units of each productivity type that operates with high and low labor inputs. There is misallocation because in most production units their labor input does not coincide with their efficient allocation. It is instructive for later discussion of actual data to emphasize the different types of misallocation in this example. One type of misallocation is that whereas in the efficient allocation each type of establishment should be of the same size, in the hypothetical data some are large and some small. I call this within-productivity types misallocation. Another type of misallocation is that whereas more productive establishments should operate larger amounts of labor, in the hypothetical data, all establishment types are on average of the same size. This is what I call across-productivity types misallocation.

Another type of misallocation is on the set of producers that operate. Whereas in the efficient allocation some establishments should not operate (or have zero labor input), in the hypothetical data they command positive input and whereas some productive establishments should command positive and large amounts of inputs, in the data these establishments do not operate. I refer to this situation as selection, and even though selection is just a special case of misallocation, we typically require more structure to assess selection effects. In the example, selection is apparent because we have characterized the efficient allocation based on a complete description of the economic environment, but note that only data and a production function specification are insufficient to assess selection effects. For this reason, many empirical analyses evaluate misallocation without distinguishing it from selection and similarly many quantitative analyses of misallocation abstract from selection effects. But note that because selection is just a special case of misallocation, it should be clear that selection effects may be linked to the same policies and institutions causing misallocation.

As discussed earlier, it is important to emphasize that in order to rationalize these hypothetical data on establishment sizes by productivity, dispersion in effective output or input distortions (or prices) across producers is essential. In particular, the hypothetical data cannot be rationalized by aggregate distortions, that is distortions that affect all producers in the same way. In other words, misallocation is generated by differences in distortions (idiosyncratic distortions) rather than common distortions across producers. It is precisely for this reason that considering production heterogeneity in this context opens up a much larger set of possible policies and institutions that can generate aggregate productivity differences.

4 The Role of Misallocation

I start with the narrower question: How important is misallocation in understanding productivity differences across countries? To assess this question, Restuccia and Rogerson (2008) studied an extension of the neoclassical growth model with production heterogeneity. The model is a version of the industry equilibrium model of Hopenhayn (1992) embedded into the neoclassical growth model. The key insight of this framework is that the set of policies that can create misallocation is very large and can be broadly characterized as *idiosyncratic* distortions—distortions that effectively affect differentially individual producer prices (inputs or outputs).

Restuccia and Rogerson (2008) consider an environment where the number of establishments is determined endogenously and hence is potentially affected by distortions. But because they focus on misallocation generated by policies that leave the aggregate capital stock constant across countries, the number of establishments is constant across their experiments. For this reason, I focus in this article on a simple version of their environment as described earlier with an exogenous number of production units. As before, a single homogeneous good is produced by a set of heterogeneous producers who differ in total factor productivity. To focus on misallocation and abstract from selection effects, I assume there is no fixed cost of operation.

I consider a generic version of policy distortions as output taxes or subsidies τ_i which are specific to each producer i:

$$(1 - \tau_i) = \frac{1}{A_i^{\theta}} \epsilon_i,$$

where θ reflects the elasticity of distortions with respect to productivity and ϵ represents distortions that are unrelated to productivity. I assume that ϵ is log normally distributed with zero mean and standard deviation σ_ϵ. Therefore, the parameters θ and σ_ϵ fully characterize policy distortions in this environment. Restuccia and Rogerson (2008) conducted quantitative experiments with either correlated distortions—distortions that apply more heavily to more (or less) productive producers—

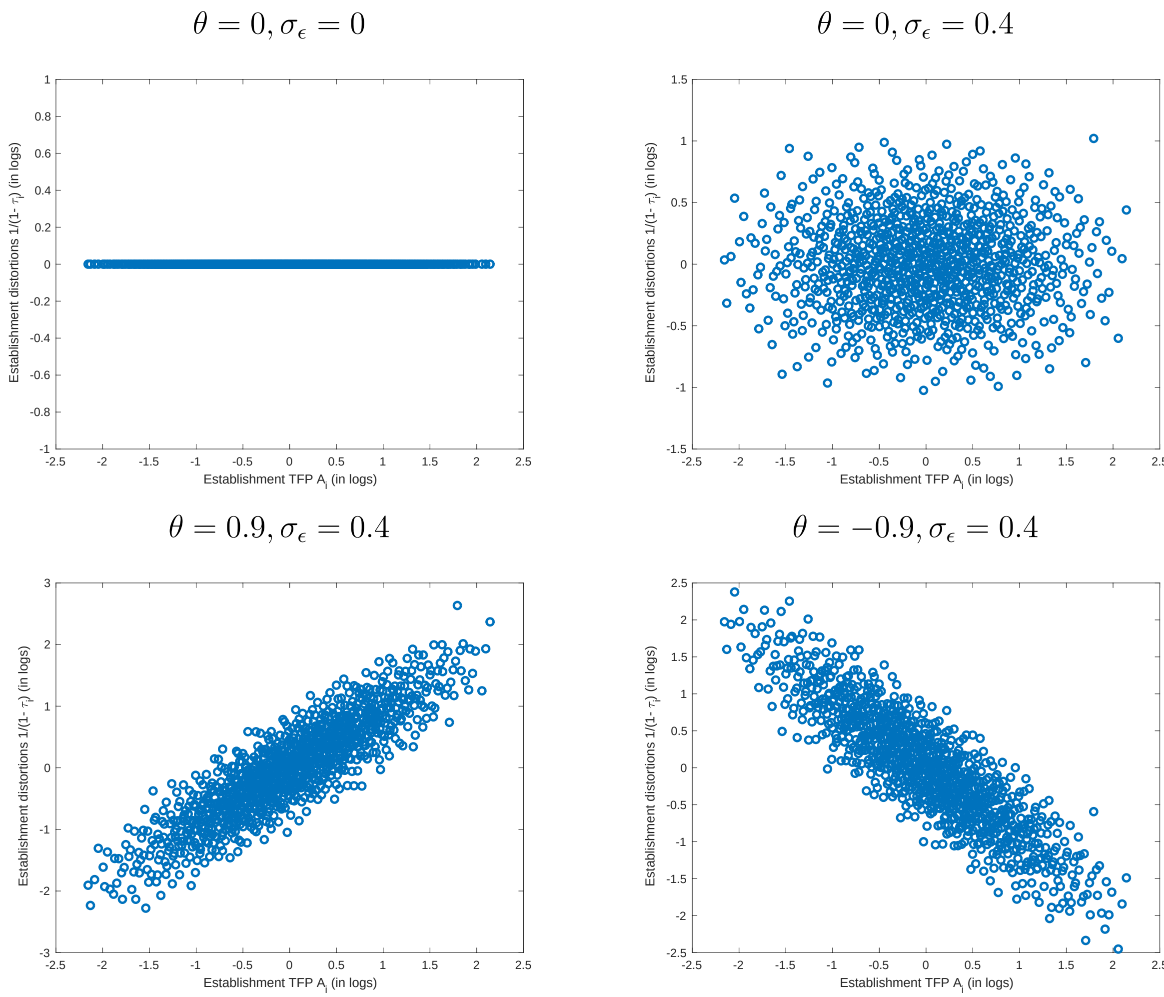
or uncorrelated distortions—distortions that are unrelated to establishment productivity. In my generic specification, θ controls the extent of correlated distortions whereas σ_ϵ controls the extent of uncorrelated distortions, and both can be present at the same time.[6] There are many possible policies and institutions that create τ differences across producers, so in this analysis, τ acts as a catch-all for all the policies, but I discuss below a set of specific policies and institutions uncovered by the literature.

Figure 2 illustrates potential patterns of distortions by reporting distortions as the log of $1/(1-\tau_i)$. Recall from our earlier discussion that variation in average products across producers is related to this measure of distortions and I discuss below that this measure is also directly related to a common measure obtained from micro data. Higher τ's imply higher distortions in this measure. The first panel represents a situation with no distortions. The second panel represents a situation with only random distortions where establishment sizes are distorted but not systematically across productivity types (only within-productivity type distortions), whereas the third and fourth panel represent a combination of random and correlated distortions when the correlation is positive and negative, respectively. In these cases, there is both within and across-productivity type distortions.

To put discipline in the analysis, I calibrate a benchmark economy with no distortions to U.S. data, where the key objects are the moments of the productivity distribution. I parameterize the productivity distribution as a log normal distribution with a mean normalized to zero and a standard deviation which I calibrate to direct estimates from the distribution of log TFP in the data from Hsieh and Klenow (2009). I simulate the economy with 1000 establishments. The standard deviation of establishment's productivity is 0.82, the 90 to 10 percentile ratio of productivity is 8.5-fold, and the 75 to 25 percentile ratio is 3.1-fold. As in Restuccia and Rogerson (2008), I set $\gamma = 0.85$.

[6] Note that even though Restuccia and Rogerson (2008) emphasized distortions in producer-level prices (idiosyncratic distortions), the policies they implement assume common taxes and subsidies among subsets of establishments and hence did not exploit the potential heterogeneity in implicit producer-level wedges that is now apparent from the micro data.

Figure 2: Patterns of Idiosyncratic Distortions—$\log \frac{1}{(1-\tau_i)}$



Notes: In the second panel, average distortions by productivity type A are not systematically related to establishment productivity, whereas in the third and fourth panel, average distortions by productivity type A are increasing and decreasing in establishment productivity, respectively.

Table 3: The Productivity Cost of Idiosyncratic Distortions

σ_ϵ	θ: -0.9	-0.5	0	0.5	0.9
0	0.96	0.98	1.00	0.91	0.50
	(0.74)	(0.40)	(0.00)	(0.40)	(0.74)
0.2	0.89	0.90	0.92	0.83	0.45
	(0.76)	(0.45)	(0.19)	(0.45)	(0.76)
0.4	0.79	0.80	0.81	0.70	0.37
	(0.83)	(0.56)	(0.39)	(0.56)	(0.83)

Notes: For each combination of parameter values for idiosyncratic distortions $(\theta, \sigma_\epsilon)$, the table reports the aggregate TFP ratio of each economy relative to the benchmark economy with no distortions; and in parenthesis, the standard deviation of $\log(y_i/h_i)$. Note that y_i/h_i is proportional to $1/(1-\tau_i)$.

I study the quantitative impact of policy distortions on aggregate TFP. In Table 3, I consider economies that are otherwise identical to the benchmark economy except in policy distortions characterized by the two parameters $(\theta, \sigma_\epsilon)$ and I report the ratio of aggregate TFP in each distorted economy relative to the benchmark economy (efficient allocation). Note that, as in Restuccia and Rogerson (2008), the set of production units and aggregate inputs in each economy are the same so aggregate output and TFP are lower in distorted economies only because the allocation of inputs across producers is deviating from the efficient allocation. Depending on the policy parameter configurations, distortions generate misallocation within productivity types by making some larger and some smaller than efficient (uncorrelated distortions generated by increases in σ_ϵ) and/or by reallocating labor across productivity types altering their optimal size (correlated distortions generated by elasticity θ different than zero).

The results from Table 3 convey a similar message as in Restuccia and Rogerson (2008). Starting with the case of $\theta = 0$, increases in σ_ϵ (random distortions) create misallocation that lowers output and TFP but the quantitative significance of empirically reasonable variations in σ_ϵ is somewhat limited, for example when $\sigma_\epsilon = 0.4$, aggregate productivity is 81 percent that of the undistorted economy.[7] When $\sigma_\epsilon = 0$, increases in θ (correlated distortions) generate potentially large effects on TFP, for instance when θ is 0.9, the TFP ratio is 0.50, which implies a productivity reallocation gain of 100 percent. But note that these different configurations of distortions are not quite comparable as the amount of resources reallocated differ among them. A commonly used measure of the extent of distortions—the amount of dispersion in $\log(y_i/h_i)$—is also limited in accurately comparing these different configurations of distortions. For instance, the cases where $(\theta = 0.5, \sigma_\epsilon = 0)$ and $(\theta = 0, \sigma_\epsilon = 0.4)$ generate similar dispersion in $\log(y_i/h_i)$, yet the reallocation gain is larger in the case of random distortions. Similarly, the results also illustrate that dispersion in $\log(y_i/h_i)$ is not generally a sufficient statistic of the productivity cost of distortions, for instance the dispersion in $\log(y_i/h_i)$ is the same for each case of θ and -θ, yet the productivity cost of the distortions is larger when the correlation is positive. The presence of both random and correlated distortions generate large productivity losses—in the case of $\theta = 0.9$ and $\sigma_\epsilon = 0.4$ a reallocation gain of a factor of almost 200 percent, implying a dispersion in $\log(y_i/h_i)$ of 0.83. A negative elasticity of distortions to TFP—expanding productive establishments at the expense of less productive establishments—also imply aggregate productivity losses, but the quantitative significance of this type of distortions is limited.[8]

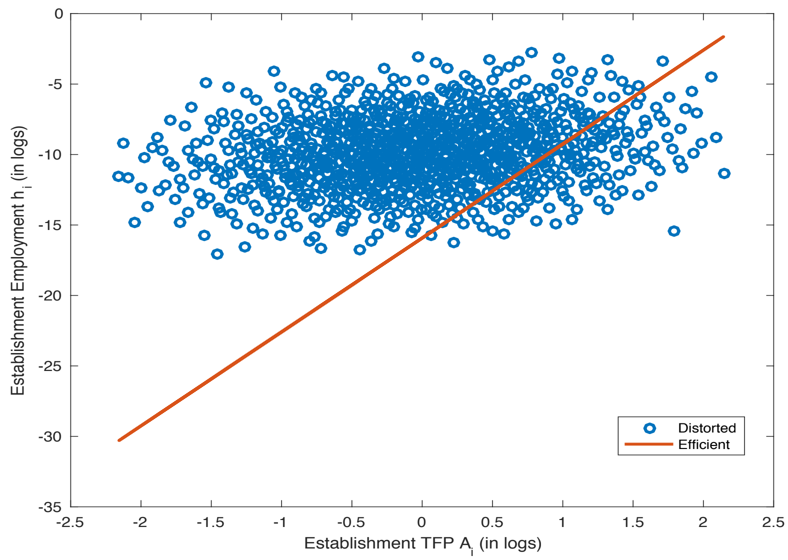
To illustrate the extent of misallocation, I report the equilibrium labor allocation that is implied by the distorted economy with $\theta = 0.9$ and $\sigma_\epsilon = 0.4$ for the simulated productive units that differ in TFP (blue dots) and contrast this allocation with the efficient allocation (red-dashed line) in Figure 3. The pattern of misallocation that arises resembles my earlier stylized characterization of misallocation for operating units. As discussed before, more structure would be needed in order to

[7] The productivity cost from misallocation can be expressed as the TFP ratio of the distorted to undistorted economy of 0.81 as in Table 3, as a productivity loss of 19 percent $(1 - 0.81)$, as the potential productivity gain of eliminating distortions of 24 percent $(1/0.81 - 1)$, or as the factor gain of 1.24-fold.

[8] Note that the quantitative impact of policy distortions in Table 3 appears larger than those reported by Restuccia and Rogerson (2008). This is due to two main reasons. First, in this article there is more dispersion in productivity across establishments, which is calibrated to the available micro data. Second, the more general characterization of policy distortions in this article allows for far more heterogeneity in idiosyncratic distortions, consistent with micro data now available from many studies.

quantify the extent to which there are also selection effects in this sample of production units.

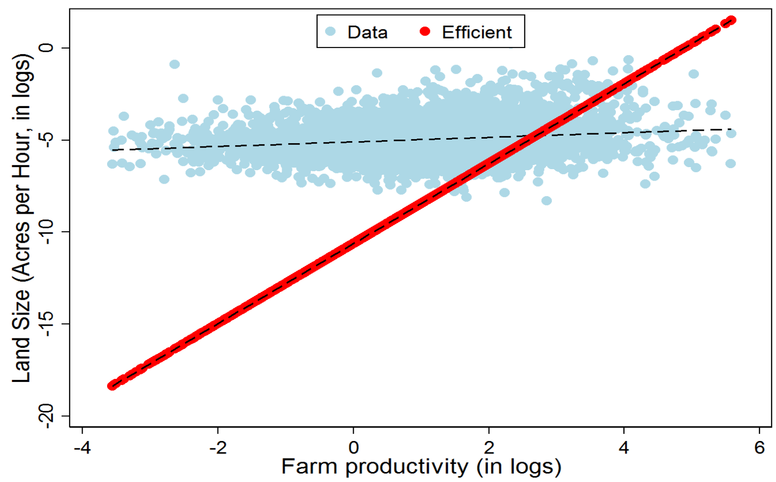
Figure 3: Distorted Allocation ($\theta = 0.9, \sigma_\epsilon = 0.4$)



Notes: Simulation of the model with 1000 establishments and distortions according to $\theta = 0.9$ and $\sigma_\epsilon = 0.4$. Blue circles represent the distorted allocation and the red line the efficient allocation.

But the question is: Is there evidence of this type of misallocation? The answer is yes, and in Figure 4, I provide an illustrative example by reporting the allocation of land across farmers in Malawi using micro data from the World Bank in Restuccia and Santaeulalia-Llopis (2017). Note that the pattern of misallocation is fairly similar between the simulated economy and the data; and the dispersion in marginal revenue products in the data (measured by the standard deviation of the log) is 0.97. Similar to the earlier finding, the reallocation gains are potentially very large in this context, a factor of more than 3-fold in agricultural productivity in Malawi (see Restuccia and Santaeulalia-Llopis (2017)). Without entering into the important details of measurement in terms of estimating TFP at the producer farm level, the underlying institution driving this allocation—which I discuss in more detail below—is a combination of an egalitarian distribution of use rights of land and effective land-market frictions that prevent the reallocation of land to best uses.

Figure 4: Land Misallocation in Malawi



Notes: Source Restuccia and Santaeulalia-Llopis (2017). Blue dots represent the data and the red dots the counterfactual efficient allocation.

The land allocation across farmers in Malawi is just one example in a very poor country. The question is, is there systematic evidence of misallocation and if so what are the consequences for aggregate productivity?

Before I describe the research on the evidence of misallocation, it is instructive to go back to the simple framework with policy distortions and note that an important insight of the basic framework is that in order to maximize aggregate output, the marginal product of factors (or average products with common production function parameters) should equalize across producers of the same good,

$$\underbrace{(1-\tau_i)\gamma\frac{y_i}{h_i}}_{\text{Value of marginal output}} = w.$$

Distortions put a wedge that affects the allocation of inputs across producers and hence lower aggregate productivity. In this context, we can define "Revenue Productivity" as

$$\text{TFPR}_i \equiv \frac{y_i}{h_i} \propto \frac{1}{(1-\tau_i)},$$

because TFPR_i equalizes across producers in the efficient allocation (more productive establishments are larger) whereas in the distorted economy TFPR_i is higher for producers with higher distortions. The revenue productivity is positively related with distortions. Higher dispersion in log TFPR_i entails more misallocation.

This insight suggests two approaches to assess the empirical relevance of misallocation, what Restuccia and Rogerson (2013) call the indirect and direct approaches. The indirect approach aims to measure deviations in log TFPR_i across producers using data on output and inputs and some basic assumptions about technology and market structure. The direct approach aims to measure specific policies and institutions that generate τ_i differences across producers. But recall that the aggregate productivity cost of misallocation depends not only on the dispersion in log TFPR but also on the distribution of productivity A_i and more generally on their joint distribution.

4.1 The Indirect Approach

Some of the early work on misallocation approached the problem in terms of trying to assess the importance of misallocation in accounting for aggregate TFP differences without trying to identify the sources of misallocation.

The empirical evidence from this approach points to large TFP loses from misallocation. Table 4 reports some of the findings from Hsieh and Klenow (2009), where the aggregate TFP gains from an efficient reallocation of resources are more than 100 percent in China and India. Large reallocation gains were also found in the United States, although perhaps some of these gains may be due to measurement and specification issues. But the main finding is that the gains from reallocation are larger in China and India than in the United States, for instance if 1998 China were to reduce the dispersion in revenue products to the level observed in 1997 United States, the aggregate TFP gains would be 72 percent.

Table 4: Misallocation and Productivity across some Countries

	SD (log TFPR_i)	TFP gains
China (1998)	0.74	115%
India (1991)	0.67	102%
India (1994)	0.67	128%
United States (1997)	0.49	43%

Notes: Source Hsieh and Klenow (2009).

Note that India features the same dispersion in log TFPR in 1991 and 1994, but the TFP gains are larger in 1994 than in 1991, and similarly, China features larger dispersion in log TFPR in 1998 than 1994 India but features lower TFP gain. As alluded earlier, these patterns point to differences in the distributions of TFP or the joint distributions of TFP and TFPR across these countries. See for example the distributions of plant-level productivity in the manufacturing sector in China, India, and the United States in Hsieh and Klenow (2009) (or the more illustrative Figure 35 of the same data in Jones, 2016, p. 56). A recurrent theme in studies of misallocation across countries is the comparability of micro data sets in different settings. For instance, in Hsieh and Klenow (2009) the distribution of plant productivity in the manufacturing sector is much different in India than in China compared with the United States, but this may be partially the result of under-representation of small firms in the Chinese survey. Similarly, many establishment surveys put restrictions on which establishments are included, potentially inducing bias in the resulting sample distributions.

There is now substantial evidence of misallocation from many other contexts and countries as

Table 5: Misallocation in African Manufacturing

	Standard deviation			
	log TFP_i	log TFPR_i	Elasticity	TFP gain
Cote d'Ivoire (avg. 2003-12)	1.24	0.65	0.42	31%
Kenya (2010)	2.41	1.52	0.52	67%
Ghana (2003)	1.75	0.95	0.44	76%
Ethiopia (2011)	1.30	0.78	0.53	163%

Notes: Statistics from Cirera et al. (2017). "Elasticity" refers to the productivity elasticity of distortions, the slope coefficient of a regression between log TFP_i and log TFPR_i.

discussed in Restuccia and Rogerson (2017). For instance, Cirera et al. (2017) use census data for the manufacturing sector in poor African countries, uncovering substantial misallocation. Table 5 reports the resulting large reallocation gains in Cote d'Ivoire, Kenya, Ghana, and Ethiopia. The table also reports the elasticity of distortions with respect to productivity which is calculated as the slope coefficient between a summary measure of idiosyncratic distortions (log TFPR) and firm productivity (log TFP). The elasticities are large, around 0.5, and much larger than the 0.09 elasticity found in the U.S. data in Hsieh and Klenow (2014).[9]

The indirect approach is useful in providing a quantitative sense of the overall importance of misallocation and identifying relevant patterns, such as where the misallocation occurs: within industries, across industries, across time and space, among others. But ultimately the method is silent about the specific sources of misallocation and identifying the causes of misallocation is key for policy analysis.

In addition, the indirect method also faces important issues of measurement and specification that can bias our quantitative estimates of misallocation. First, most studies of the manufacturing sector rely on revenue or sales data at the plant level and hence some assumptions are needed on the

[9]See also Pagés (2010) for evidence from Latin American countries.

demand structure to separate price and output from revenue.[10] Second, the specification of the production structure is important as heterogeneity in technology across producers can in principle rationalize any dispersion in marginal products (e.g., Asker et al., 2014). In addition, with just cross-sectional data, it is difficult to separate distortions from shocks in the presence of adjustment costs. David and Venkateswaran (2017) use annual panel data to identify the sources of dispersion in the marginal product of capital across producers. The key insight is that whereas distortions and adjustment costs can equally rationalize cross-sectional dispersion in marginal products, distortions and adjustment costs have different implications for the autocorrelation of investment. This insight provides identification of the relative strength of distortions versus adjustment costs in the data. Using data for China and other countries David and Venkateswaran (2017) find a larger role for distortions in poor economies. Third, inputs may be measured with error and the role of measurement error has now been studied by Bils et al. (2017) using panel data. While there appears to be important measurement error in the data, specially in the U.S. data, the main finding of the relative gain of reallocation between India and China relative to the United States appears robust.

In sum, a better understanding of the extent of misallocation requires more data—especially comparable panel micro data across countries—and more exploration of the relevant demand, technology and other features of the economic environment.

4.2 The Direct Approach

The direct approach quantifies the role of specific policies and institutions on misallocation, such as selective regulations and discretionary provisions, financial frictions, selective industrial policy, trade restrictions, among many others. The approach requires good empirical measures of the

[10] This is not an issue when plant-specific price deflators are available, see for instance Eslava et al. (2013) for a dataset from Colombia. Nevertheless, the comparisons across plants often involve producers of different goods. See Restuccia and Santaeulalia-Llopis (2017) for an analysis of the agricultural sector, where quantity produced of specific (homogeneous) goods is available.

policies and additional model structure.

There are many applications of this approach which directly reflect the perverseness of misallocation in actual policy and institutional environments. Restuccia and Rogerson (2017) discuss this literature in more detail. I simply refer to a few examples, starting with the role of regulations. An early example of studies of regulation creating misallocation is the impact of firing costs on productivity in Hopenhayn and Rogerson (1993). Firing costs are a prevalent policy in developed and developing countries and are amenable to measurement as the policy can be expressed as a proportion of wages. Firing costs—acting as an adjustment cost created by policy—generate misallocation because the policy creates inaction in establishment-level decisions with respect to productivity by postponing hiring and firing decisions. Firing costs equivalent to 1 year's wages—as is prevalent in some OECD and developing countries—implies an aggregate TFP loss of 2 percent. Firing costs equivalent to 5 year's wages implies a dispersion in log TFPR_i of 0.19, a correlation log TFPR_i and log TFP_i of 0.76, and an aggregate TFP loss of 8 percent, see Hopenhayn (2014).

Regulations often take the form of size-dependent policies as emphasized in Guner et al. (2008). These are distortions that are related to the size of the establishment (e.g. number of employees). For example, many countries impose taxes or regulations to establishments above a certain size. These policies can have large effects on the number of establishments and average size, but the quantitative effects on aggregate TFP are relatively small. For example, in Guner et al. (2008), size-dependent distortions that imply a 20 percent reduction in average establishment size generate an aggregate TFP loss of 3.6 percent when aggregate TFP is defined as efficiency units of managers whereas less than 1 percent as measured TFP. As discussed earlier, dispersion in idiosyncratic distortions is key for misallocation and the associated productivity costs. Size-dependent policies generate limited dispersion of distortions since there is reallocation of resources between affected and unaffected establishments but not within them; and dispersion in an inaction zone, a region of productivity where establishments stay just below the size threshold.

Another well-researched area is the role of financial frictions, see for instance, the survey in Buera et al. (2015). Financial frictions—for example collateral constraints—generate dispersion in the marginal product of capital across producers and hence misallocation. I emphasize that while financial frictions is a country-level institution, it generates idiosyncratic effects—effects that are heterogeneous across producers. In fact, the pattern is such that credit constraints disproportionally affect more productive producers that should operate at a larger scale and so the implicit wedges it generates are positively correlated with producer-level TFP.

Overall, the results of the direct approach have essentially left a challenge in that the literature has not identified a single or a small set of sources that can account for the bulk of productivity differences. Any measured policy is shown to have some limited effect, and so many different policies and institutions are needed to account for the data. It is also possible that many sources of policy distortions are correlated and interact, see for instance Moscoso Boedo and Mukoyama (2012) analyzing the cost of entry and firing costs across countries from the Doing Business database of the World Bank and Ranasinghe and Restuccia (2018) for the role and interaction of financial frictions and the rule of law using cross-country establishment-level data from the World Bank Enterprise Survey.

The are a couple of exceptions to this general conclusion that are relevant to discuss: First, the role of land market institutions in agriculture that are shown to generate substantial productivity losses (e.g., Adamopoulos and Restuccia, 2014). Second, analyses that focus on changes in policies over time in specific contexts, instead of differences in policies across countries at a point in time, that are able to account for a substantial portion of the changes in the data.

Land institutions in many poor countries are characterized by a lack of well-defined property rights over land. Instead land-use rights are distributed at the local level in a fairly uniform basis with varying degrees of difficulty to reallocate/adjust operational scales. The resulting pattern is such that land is not allocated to best uses, leading to small farm sizes, misallocation of other factor inputs, and potentially also preventing the adoption of best practices and investment in farm operation. The best evidence points to substantial land misallocation with severe negative consequences for aggregate agricultural productivity in poor and developing countries. I discuss two examples. The first example is from Malawi where there is excellent micro data from the World Bank as discussed earlier. In Malawi, land institutions fit the broad pattern described above and land allocations are essentially not related to farm productivity (see again Figure 4). The consequences for aggregate agricultural productivity are very large. An efficient reallocation of factors across existing farmers in Malawi can increase aggregate agricultural productivity by a factor of 3.6-fold. Similarly, a reallocation of factors among farmers operating without marketed land—those operating only their use-right land—to reduce the dispersion of revenue products to the level observed in farms operating marketed land—those operating land acquired formally or informally through purchases or rentals—generates an aggregate agricultural TFP gain of 160 percent.

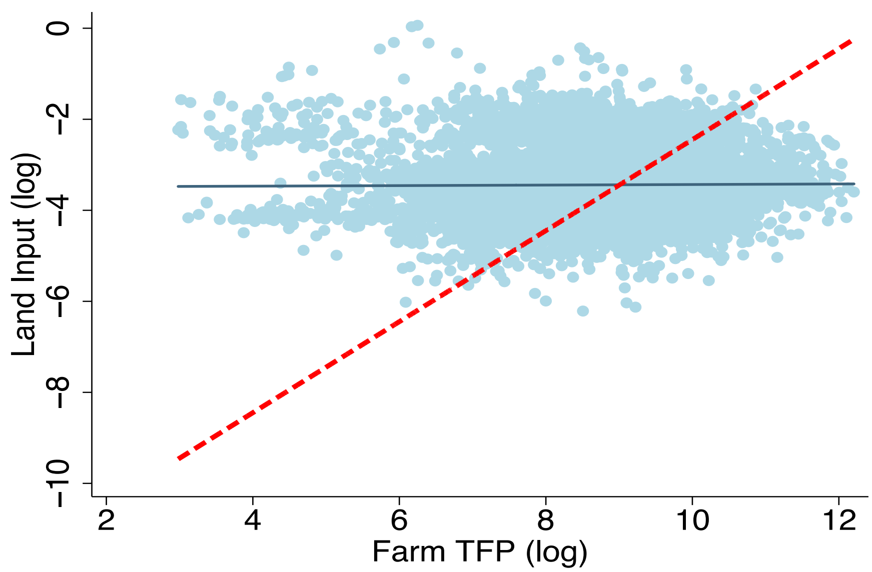
The second example is from the interesting context in China where the land market institution is entangled with severe restrictions to migration across space as described in Adamopoulos et al. (2017). The resulting pattern of misallocation, reported in Figure 5 Panel A, is again such that the land allocation is not systematically related to farm TFP, although in China we observe more within-farm TFP misallocation, suggesting that migration restrictions serve as an additional source of misallocation in China.[11]

I emphasize that the pattern of distortions that emerges from the data is one of severe misallocation. Summarizing the implicit distortions facing farmers as output distortions and constructing the implied measure of log TFPR_i, the dispersion in log TFPR_i across farmers is large both in Malawi (0.97) and China (0.78). In addition, log TFPR_i is strongly correlated with log farm TFP_i (0.86 in China), implying that the more productive farmers face the more severe distortions as they cannot

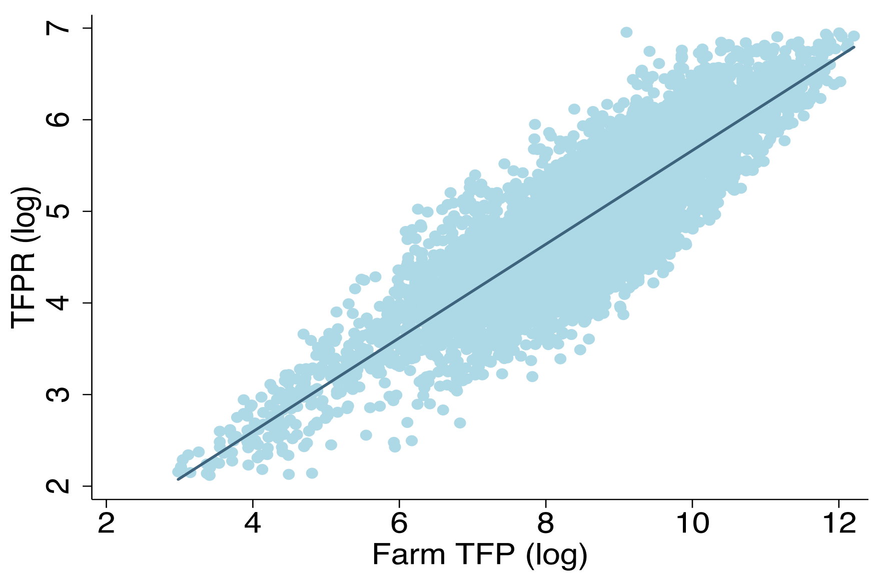
[11] An interesting aspect of the data from China is that it is a panel of farms for about 10 years, allowing robustness analysis with respect to potential transitory shocks in output and measurement error in inputs and outputs. In addition, despite reforms in other sectors, land market institutions have remained essentially the same until 2003 and so is the resulting misallocation in the data over time, see Adamopoulos et al. (2017).

Figure 5: Land Misallocation in China

Panel A: Land Allocation by Farm TFP



Panel B: Implicit Agricultural Distortions



Notes: Source Adamopoulos et al. (2017). The implied distortions in the panel data for China are large as reflected by the large dispersion of marginal revenue products, σ(log TFPR)=0.78, and the high correlation of distortions with productivity ρ(log TFPR,log TFP)=0.86.

grow their farm size (see Figure 5, Panel B).[12] This pattern that distortions are positively correlated with productivity is pervasive in agriculture in poor countries but is also found in other sectors, see for instance Hsieh and Klenow (2014), Bento and Restuccia (2017), Cirera et al. (2017), among others. This systematic pattern is key in assessing the broader implications of misallocation on productivity that I discuss in the next section.

The second exception is the type of analysis where a specific policy change generates sizeable effects that can account for the bulk of observed changes in the data. For example, Pavcnik (2002) studies a comprehensive trade reform in Chile using plant-level data, exploiting differential exposure to external competitive pressure. Reallocation of resources from less to more efficient plants contributed substantially to aggregate productivity growth during the period. Adamopoulos and Restuccia (2015) study a comprehensive land reform in Philippines using panel data of farmers before and after the reform. The reform entailed a cap in maximum land holdings in addition to government intervention in the land market by directing excess land to landless/smallholders and restricting reallocation. On impact, the land reform generates a reduction in farm size of 34 percent and a reduction in aggregate agricultural productivity of 17 percent, consistent in magnitude with the observed declines in the data. The government intervention in the land market is key for the overall impact of this land reform: allowing instead for market reallocation of the excess land from the cap in land holdings generates only 1/3 of the negative effects on size and productivity.

[12] To illustrate that the large reallocation gains arise because of more severe distortions in agriculture instead of sectoral differences in the distribution of TFP, I simulate producers taking the distribution of productivities in U.S. manufacturing from Hsieh and Klenow (2009) and applying the distortions in the United States and China reported in Hsieh and Klenow (2009). I find a relative reallocation TFP gain (China to United States) of a factor of 1.3-fold. If instead I apply China distortions in agriculture—which feature higher TFPR dispersion and stronger correlation with productivity—the relative gain is 4-fold. Hence, there are much larger distortions in agriculture in China.

5 Broader Consequences of Misallocation

The last issue I discuss relates to the broader consequences of misallocation. The early misallocation analyses assumed a fixed distribution of productivity across establishments which was kept constant across countries. But the key insight of the current work on misallocation is that the policies and institutions causing misallocation can generate larger effects on aggregate productivity by altering the productivity distribution via the technology and selection channels discussed earlier.[13]

Considering the broader consequences of misallocation is important because the evidence suggests that the distribution of establishment-level productivity differs substantially across countries. A simple accounting calculation using micro and aggregate data for the manufacturing sector in India and the United States suggest that TFP can be roughly decomposed as 1/4 arising from misallocation, 1/4 from selection, and 1/2 from technology; implying that both selection and technology shifts are essential in accounting for low productivity in developing countries.[14]

The question is then, can the policies and institutions generating misallocation, imply effects on the selection and technology channels? The short answer is yes. Note that one of the key patterns I have emphasized that emerges from the data and many of the policies and institutions that create misallocation is a high degree of correlation between distortions and producer-level TFP so more productive producers face larger distortions. This implies a lower return to being productive and hence thwart efforts such as the adoption of better technologies or investments in productivity. Similarly, the pattern of distortions can affect occupational choices and hence distort selection patterns.

[13] See, for instance, Da-Rocha et al. (2017) for a general framework where the productivity distribution is endogenous and depends in particular on policy distortions.

[14] To perform this calculation, I again parameterize the distribution of productivity and distortions. Keeping the productivity distribution as in the U.S. data but imposing the distortions in India, I find that the productivity gains are only 30 percent, half of the 60 percent gains when removing distortions in India's distribution. Since Hsieh and Klenow (2009) argue that the 60 percent gain is about half the difference in manufacturing TFP between India and the United States, I attribute one half to technology, one quarter to selection, and the remaining one quarter to misallocation.

There are a number of works, both empirical and quantitative, that have explored the connection between misallocation and technology/selection channels. Three examples of research connecting policies and institutions generating misallocation with effects on selection are the following. First, studies emphasizing the role of financial frictions.[15] In a typical framework with perfect credit markets, there is a unique threshold productivity above which individuals become entrepreneurs and capital is allocated among them according to productivity, with more productive entrepreneurs operating larger amounts of capital. But when credit markets are imperfect—as is often the case in developing and poor countries—both the allocation of capital among entrepreneurs and selection into entrepreneurship are affected. In particular, not only productive entrepreneurs with insufficient capital operate at a suboptimal scale (creating capital misallocation), but also in models of collateral constraints, selection into entrepreneurship is distorted in a way that some wealthy but not so productive individuals find it profitable to become entrepreneurs while some very productive but not wealthy individuals do not enter entrepreneurship.[16] The quantitative effects of financial frictions on aggregate productivity can be substantial because of occupational choice distortions and hence, in this setting, the selection channel is important.

Second, studies emphasizing the role of trade. Most empirical studies on the effects of trade reforms on aggregate productivity find that selection (through the effect on entry and exit) is an important contributor to aggregate productivity gains, see for instance, Pavcnik (2002), Trefler (2004), Eslava et al. (2013), among many others. For example, Khandelwal et al. (2013) study the elimination of export quotas by the United States, the European Union, and Canada in 2005 on Chinese textile and clothing. They find that the resulting productivity increase after the elimination of the quotas is accounted for by unproductive producers exiting the market. This selection effect is

[15] See, for instance, the review in Buera et al. (2015).

[16] The importance of financial frictions for misallocation depends on the extent to which individuals can save themselves out of the financial constraint, an ability that depends greatly on the persistence of entrepreneurial ability. See for example Buera and Shin (2011), Moll (2014), and Midrigan and Xu (2014). Habib (2017) connects financial frictions with information frictions on entrepreneurial ability, providing a larger role to financial frictions even in the presence of high persistence.

explained by the discretionary allocation of quotas by the Chinese government—mainly to not very productive state-owned enterprises. Hence, in this context, selection played a substantial role in the productivity gains from eliminating distortions.

Third, studies emphasizing the role of land market institutions. A recent body of research has established a connection between restrictive land market institutions in many poor and developing countries and misallocation in the agricultural sector. As discussed earlier, an important property of the implied distortions across farmers is that productive farmers are affected the most as their operational scale is severely restricted by the inability of operating at a larger scale (through rentals or purchases of land). These restrictions could affect the selection into farming. Adamopoulos et al. (2017) use micro panel data from China to assess the quantitive impact of distortions in agriculture on selection. The authors show that a static TFP gain of eliminating distortions in the agricultural sector 45 percent translates into a 200 percent gain when selection is taken into account.

Other research emphasizes the connection of misallocation with effects on technology. Intuitively, if distortions penalize the most productive producers, then, in a dynamic setting distortions reduce the return to adopting the most productive technologies or discourage investment in productivity. For example, Bustos (2011) studies the effect of a trade liberalization on the technology upgrading of firms, finding a substantial role for the technology channel. Similarly, Ayerst (2016) emphasizes the effect of idiosyncratic distortions on technology adoption lags across countries.

There is also substantial research emphasizing the effect of distortions on firm investment in productivity.[17] I discuss one such a framework from Bento and Restuccia (2017), a standard monopolistic competition model, building on Hsieh and Klenow (2009), augmented to include endogenous entry of establishments and investment in entry-level and life-cycle productivity of establishments. The main emphasis in the analysis is on the aggregate productivity implications of differences in the

[17] See, for instance, Bhattacharya et al. (2013), Gabler and Poschke (2013), Ranasinghe (2014), Hsieh and Klenow (2014), Guner et al. (2018), among others.

correlation of distortions with establishment-level productivity. I focus here on two opposing cases: (1) the United States, where this correlation is small (0.09); and (2) India, where the correlation is high (0.5). Bento and Restuccia (2017) document a strong negative relationship between the productivity elasticity of distortions and GDP per capita across a relatively large set of countries.

The key results are summarized in Table 6. First, distortions have a large negative impact on establishment size. For instance, increasing the productivity elasticity of distortions from 9 to 50 percent implies a reduction in average establishment size from 22 workers to 3. This implication is consistent in magnitude with what is found empirically in a comprehensive dataset of average establishment sizes for the manufacturing sector constructed in Bento and Restuccia (2017). Second, correlated distortions affect negatively investment in productivity both upon entry—from a normalized level 1 to 0.42—and during the life cycle of establishments—from an annual growth rate of productivity of 5 to 2.1 percent. The reduction in life-cycle productivity growth is consistent with the patterns documented in Hsieh and Klenow (2014) on the life cycle productivity of plants in India vis-a-vis the United States.[18] Third, the effect of correlated distortions on aggregate productivity is largest through misallocation (standard channel) and entry investment, which implies a shift in the mean of the productivity distribution. For instance, correlated distortions reduce aggregate output to 0.63 of the benchmark economy, and the entrant-investment channel reduces it further to 0.47. In this model, the effect of lower life-cycle productivity growth on aggregate output is mitigated by an increase in entry and reduced dispersion in establishment productivity. This suggests, going forward, that the more likely channels accounting for productivity gaps across countries involve effects via selection and shifts in mean productivity as a technology channel.

[18]More generally, distortions generating misallocation can have effects on productivity growth. Some work along these lines includes Poschke (2009), Mukoyama and Osotimehin (2016), and Chen and Restuccia (2018).

Table 6: Productivity Investment and Firm Dynamics

Prod. elasticity of distortions:	0.09 (US)	0.50 (India)
Average Establishment Size	22	3
Entrant Productivity	1.00	0.42
Life-cycle growth (%)	5.0	2.1
Prod. investment share (%)	13.5	5.4
Decomposition of agg. output:		
(a) Static misallocation	1.00	0.63
(b) Exo. life-cycle growth	1.00	0.91
(c) Endogenous life-cycle growth	1.00	0.70
(d) Entrant investment	1.00	0.47

Notes: Source Bento and Restuccia (2017).

6 Conclusions

Productivity is at the core of cross-country differences in economic structure, structural change, and aggregate outcomes. Misallocation of factors of production across heterogeneous production units is prevalent in developing and poor countries and quantitatively important in accounting for productivity gaps across countries. Although identifying the sources of misallocation is essential for policy analysis, the literature has not been able to isolate a single source of misallocation that can account for the bulk of differences. Nevertheless, the literature has identified a common pattern of distortions, whereby there is a strong association between distortions and producer-level productivity. This property of distortions in essential in linking misallocation—the policies and institutions creating misallocation—with technology and selection channels in accounting for productivity differences. I believe this is an essential area for future work.

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