

A detailed anatomy of factor misallocation in India

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ABSTRACT: We provide complements to the results of Duranton, Ghani, Grover Goswami, and Kerr (2015) along several dimensions. We first expand our methodology and provide two important decompositions for our main indices. Our main result is that factor and output misallocation across districts is, at least, as important as misallocation within districts. Second, we provide an exploration of the service sector that complement our earlier work on manufacturing. Our analysis shows that labour plays a fundamental role for misallocation in services whereas land was the determining factor for manufacturing. Third, we expand our earlier work on the effects of policies on misallocation by looking at a much broader range of policies and find strong evidence of their effects on misallocation. Finally, we take steps towards the identification of the causal effect of misallocation on output per worker by developing a novel instrumental variable approach and a simulation approach that allows us to check the consistency of our empirical results.

Key words: agglomeration, firm selection, productivity, cities

JEL classification: C52, R12, D24

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1. Introduction

We provide complements to the results of Duranton *et al.* (2015) along several dimensions:

- We expand our methodology and provide two important decompositions for our main indices.
- We implement empirically these two decompositions in a variety of contexts.
- We provide an exploration of the service sector that complement our earlier work on manufacturing.
- We expand our earlier work on the effects of policies on misallocation by looking at a much broader range of policies.
- We take steps towards the identification of the causal effect of misallocation on output per worker.
- We provide simulation results to check the consistency of our empirical results.

These extensions, complements, and alternative applications are important for a number of reasons. First, the methodology proposed by Duranton *et al.* (2015) is novel. Given its broad potential applicability, it certainly warrants further explorations. The two developments that we propose here are of particular interest. The first is a factor decomposition, which shows precisely, how, in theory, factor misallocation affects output misallocation. This decomposition also implies an extremely sharp quantitative prediction regarding the sum of the coefficients in the regression of output misallocation on the misallocation of the different factors of production. We can verify this prediction empirically. This verification provides a further validation of our approach and an important insight about the role of land in manufacturing.

The second decomposition is a within/between group decomposition. Our initial approach was concerned with a single level of aggregation: Indian districts. Our decomposition shows how misallocation at different levels of aggregation can be linked

to each other. This within/between decomposition shows that aggregate misallocation sums the weighted sum of the misallocation of each group (e.g., each district) and a between-group misallocation term (e.g., misallocation between districts). That allows us to distinguish between different forms of misallocation. The high level of misallocation in India documented initially by Hsieh and Klenow (2009) could be due either to too many workers residing in poorly productive areas or to more productive establishments everywhere being unable to expand their employment. These are two very different forms of misallocation. They probably call for different corrective policies. It is important to distinguish between them and measure them appropriately. The decomposition we propose here is a bridge between our earlier approach, which was uniquely concerned with misallocation within districts, and the recent work of Hsieh and Moretti (2015), which focuses solely on misallocation across locations.¹

We also expand our previous empirical work in several directions. The first regards the service sector. Studying manufacturing presents a number of advantages, including greater data availability, estimation methods that have been used for a long time, and its possible unique importance for development. However, it represents only a small share of the economy in India. It is important to expand our analysis to services even though data is sparser and arguably more difficult to exploit when it comes to estimating production functions.

In Duranton *et al.* (2015), we assessed the effects of two policies on misallocation. These were the repeal of the Urban Land Ceilings Regulation Act (UCLRA) and changes in stamp duty taxation. Studying narrow but well-defined policies, which are expected to affect primarily the land market, is useful. This is all the more useful when, like in the case of the repeal of UCLRA, a good case can be made that policy changes were exogenous. It remains unclear however how much external validity there is in our initial exploration of these two policies. Here, we generalise our previous work to two sets of state-level

¹See also Hsieh and Klenow (2014) for evidence regarding the life cycle of plants and the lack of growth of Indian establishments as they age. These facts are consistent with a major role for misallocation within districts.

policies and three industry policies. To explore them in a consistent framework, we work at the level of individual industries within states instead of aggregating industries within districts. This alternative level of aggregation also provides us with a useful check on our earlier results. More specifically, the five policies we study are land reforms (Besley and Burgess, 2000), labour reforms (Besley and Burgess, 2004), industry delicensing, industry tariff changes, and the liberalisation of foreign direct investment (all studied by Aghion, Burgess, Redding, and Zilibotti, 2008).

Finally, our earlier exploration was mostly descriptive in spirit. Here we take two steps towards a more causal analysis. Finding instruments for misallocation when trying to assess how misallocation affects output per worker is intrinsically difficult. For instance, the policy changes we explore above affect misallocation. Through changes in misallocation, we expect these policies to affect output per worker. However, it is difficult to argue that these policies will affect output per worker only through misallocation (and other channels that can be controlled for). If these policies have a direct effect on productivity, they cannot be used appropriately as instruments for misallocation. We expect a similar negative argument will apply to any contextual variable. Some local characteristics will affect district misallocation but we also suspect they will affect local productivity directly. Instead, we use past misallocation to instrument for current misallocation. While this instrument might fail because past misallocation may be correlated with contemporaneous determinants of output per worker, this bias should remain small when we control for permanent characteristics of districts through district fixed effects. Additionally, we also use as instruments predictors of misallocation based on the industry composition of manufacturing in each district.

We also report results from simulations that seek to mimic the type of economy that we study. That is, we consider an hypothetical set of establishments for which the production function is as we estimate and for which factors and estimated productivity are as in the data we use. Then, we re-simulate such an economy by changing marginally the misallocation of one factor. This allows us to assess the effect of this marginal change on

output per worker. The main drawback is that implementing this approach without too much complexity requires imposing strong distributional assumptions.

2. Misallocation: a primer

This section provides a quick refresher for the concepts and main notations used in Duranton *et al.* (2015). Please refer to this paper for further details.

As argued in Duranton *et al.* (2015), the productive efficiency of an economy depends on three main proximate factors. The first is the amount of inputs which are available. The importance of factor and capital deepening was highlighted and first articulated by Solow (1956). The second proximate factor of growth is the level of technological development and the ability of an economy to generate more output out of the same inputs. While the development of better technologies has been a focus of an extremely large literature for many years, Romer (1990) was an important milestone, linking the development of new technologies and factor accumulation. The third proximate factor of growth is the ability of an economy to allocate more inputs to more productive establishments.² In most economic models involving production by heterogenous producers, the most productive ones should be given access to more inputs given their ability to generate proportionately more output. In a frictionless economy, we expect an efficient allocation of inputs across establishments. Establishments in real economies face serious frictions that lead to an inefficient factor allocation. Although this idea has been around for a long time, Restuccia and Rogerson (2008) and Hsieh and Klenow (2009) should be credited for articulating it in a formal model and for making the case regarding its quantitative relevance.³

In Duranton *et al.* (2015), we extend the misallocation methodology initially provided by Olley and Pakes (1996). The production function of establishment i is:

$$Y_i = e^{\varphi_i} T_i^\alpha K_i^\beta L_i^\gamma, \quad (1)$$

²We refer to production units as establishments to be consistent with the data we use below.

³We think of factor accumulation, technological improvement, and factor allocation as proximate factors of growth. In turn, they result from deeper causes of growth such as institutions, culture, and policies.

where Y_i is value added, which we refer to as output, φ_i is the (log) total factor productivity of establishment i , T is land and buildings, K is other fixed assets, and L is labour. Duranton *et al.* (2015) explicitly separate between land and buildings and other fixed assets such as machines because this distinction is important in their (manufacturing) context.

Next, define the share-weighted aggregate productivity of a group g of n_g establishments as:

$$\Phi_g = \sum_{i=1}^{n_g} s_{ig} \varphi_i, \quad (2)$$

where s_{ig} the share of establishment i in group g . For now we consider the share of establishment i to be its output share: $s_{ig} = \frac{Y_i}{\sum_{j=1}^{n_g} Y_j}$.

Following Olley and Pakes (1996), it is particularly insightful to note that:

$$\Phi_g = \bar{\varphi}_g + \sum_{i=1}^{n_g} (s_{ig} - \bar{s}_g)(\varphi_i - \bar{\varphi}_g) = \bar{\varphi}_g + n_g \text{cov}(s_{ig}, \varphi_i), \quad (3)$$

where $\bar{\varphi}_g \equiv \frac{1}{n_g} \sum_{i=1}^{n_g} \varphi_i$ is the unweighted productivity mean across establishments in group g and $\bar{s}_g (= 1/n_g)$ is the mean establishment share. Then, we can define misallocation in group g as

$$M_g = -(\Phi_g - \bar{\varphi}_g) = -n_g \text{cov}_g(s_{ig}, \varphi_i). \quad (4)$$

This misallocation index is a negative function of the covariance between the share and productivity of establishments so that misallocation is minimised when the covariance between shares and productivity is highest. Relative to usual practice in past work and to ease the reading of our results, equation (4) multiplies the ‘misallocation’ covariance term by minus one so that an increase in the index corresponds to an increase in misallocation. It is useful to note that $M = 0$ corresponds to output being uncorrelated with establishment productivity while more negative values correspond to less misallocation (and positive covariances between output and productivity). The measure of allocation defined by equation (4) is also equal to the difference between un-weighted and weighted productivity, where the weights are the establishment shares of output.

Relative to extant literature, Duranton *et al.* (2015) expand the OP approach in two directions. First, the shares used above in the computation of misallocation are output

shares. It is obvious that alternative misallocation indices can be computed by weighting establishments by their share of any given factor of production instead of output. That is, we can build measures of allocation efficiency for output, M^Y , employment, M^L , land and buildings, M^T , other fixed assets, M^K , or any combination of these. These different measures of misallocation are conceptually distinct. For instance, a given factor of production might be more misallocated than another depending on the relative frictions affecting input markets.

The second innovation of Duranton *et al.* (2015) is to compute misallocation indices for subnational units. At this point it is important to clarify what a measure of misallocation within a district captures. Loosely speaking, computing the misallocation of, say, employment in each district separately yields a measure of the misallocation of workers within each district, taking as given the distribution of employment across districts so that the misallocation of employment within districts is only one component of the misallocation of employment in the entire country. We return to this important point below in section 3.2.

Then, Duranton *et al.* (2015) estimate three separate regressions. The first is a long difference-in-difference regression that relates changes in misallocation to policy changes:

$$\Delta M_d = A_0 + A_1 \Delta P_d + X_d A_2 + \epsilon_d, \quad (5)$$

where ΔM_d is a change in misallocation (for output or any given factor) in district d , P_d is a policy indicator variable for district d , X_d is a vector of district d characteristics that might be correlated with P_d , and ϵ_d is an error term. More specifically, Duranton *et al.* (2015) explore the effects of two policy changes on the misallocation of output and the misallocation of land and buildings. The first is the abrupt repeal of the Urban Land Ceilings Regulation Act (ULCRA) by the federal government of India in 1999. The second is the changes in stamp duty taxation in Indian states over 1989-2010. Because changes in stamp duties (a tax that needs to be paid when transacting real property) may have been determined simultaneously with changes in misallocation, we use an extensive set of control variables. The case for the exogeneity of the repeal of ULCRA is much stronger. We

nonetheless control for possible confounding factors in this case as well. Both policies are associated with changes in local misallocation. This provides an important check on our computed measures of misallocation. This also shows how misallocation may be caused by policies that create stronger frictions in input markets.

In the analysis below, we return to regression (5) and explore a broader range of policies including land and labour reforms over 1985-1997 and the liberalisation of industry licences, trade, and foreign direct investment over the same period.

The second estimation performed by Duranton *et al.* (2015) is a regression of output misallocation on factor misallocation:

$$M_d^Y = B_0 + B_1 M_d^L + B_2 M_d^T + B_3 M_d^K + \mu_d, \quad (6)$$

where the dependent variable is output misallocation in district d and the three explanatory variables are misallocation indices for the three inputs, employment (L), land and buildings (T), and other fixed assets (K). The first main result associated with this regression in Duranton *et al.* (2015) is that output misallocation is strongly associated with input misallocation. A one unit increase in factor misallocation typically leads to about a one unit increase in output misallocation in Indian districts. Below we provide a new way to interpret this result by showing how output misallocation can be expressed as a function of factor misallocation. When establishments operate with constant returns to scale, a one-for-one increase in output misallocation should follow from an increase in misallocation for all factors. Below, we verify this result further using data for services and manufacturing data used at a level of aggregation different from Duranton *et al.* (2015). The second main result of Duranton *et al.* (2015) is that the misallocation of land and buildings plays a particularly important role to explain the misallocation of output in manufacturing. We confirm in part this result obtained for districts when using instead specific industries at the state level. We also provide results for services. This time, the fundamental driver of output misallocation is the misallocation of employment, while the misallocation of land and buildings plays little to no role.

The final estimation performed by Duranton *et al.* (2015) is a regression of log output per workers y_d on factor misallocation:

$$y_d = B_0 + B_1 M_d^L + B_2 M_d^T + B_3 M_d^K + v_d. \quad (7)$$

Duranton *et al.* (2015) find large effects of factor misallocation on output per worker. Below, we confirm these large effects for a different treatment of manufacturing and for services. We also confirm that the misallocation of land and buildings plays a fundamental role in manufacturing while it has a much smaller effect on output per worker in services.

3. Two decompositions

3.1 Factor decomposition

This first decomposition is helpful to understand regression (6) and be able to interpret its results further.

Dropping group indices for simplicity, recall that output misallocation can be written as:

$$M^Y = -n \text{cov}(s_i^Y, \varphi_i) = - \sum_{i=1}^n s_i^Y (\varphi_i - \bar{\varphi}), \quad (8)$$

where $s_i^Y = Y_i/Y = Y_i/\sum_j Y_j$ is the share of output of establishment i in total output. Recall that output for establishment i is given by $Y_i = e^{\varphi_i} K_i^\alpha L_i^\beta T_i^\gamma$. Profit maximisation implies $r K_i = \alpha Y_i$, $w L_i = \beta Y_i$, and $R T_i = \gamma Y_i$ where r is the interest rate on other fixed assets, w is the wage, and R is the rental rate of land and buildings. Aggregating across all establishments, it is easy to obtain $r K = \alpha Y$, $w L = \beta Y$, and $R T = \gamma Y$ where $K \equiv \sum_j K_j$, $L \equiv \sum_j L_j$, and $T \equiv \sum_j T_j$ are the aggregate values of other fixed assets, labour, and land and buildings, respectively. When establishments operate under constant returns to scale (i.e., $\alpha + \beta + \gamma = 1$), free entry then implies $Y_i = r K_i + w L_i + R T_i$. Then it obviously follows from these simple results that

$$\begin{aligned} s_i^Y &= \frac{r K_i}{Y} + \frac{w L_i}{Y} + \frac{R T_i}{Y} = \frac{r K_i}{\frac{r K}{\alpha}} + \frac{w L_i}{\frac{w L}{\beta}} + \frac{R T_i}{\frac{R T}{\gamma}} = \frac{\alpha K_i}{K} + \frac{\beta L_i}{L} + \frac{\gamma T_i}{T} \\ &= \alpha s_i^K + \beta s_i^L + \gamma s_i^T, \end{aligned} \quad (9)$$

where s_i^K , s_i^L , and s_i^T are the shares of establishment i in other fixed assets, labour, and land and buildings respectively. Using equation (9), it is easy to rewrite equation (8) as:

$$M^Y = \alpha M^K + \beta M^L + \gamma M^T, \quad (10)$$

where M^K , M^L , and M^T are indices of factor misallocation that correspond to M^Y but use the factor shares instead of output shares. We can note that this is a theoretical analogue to regression (6)

Hence, by regressing output misallocation on factor misallocations, we should recover the factor shares α , β , and γ . Interestingly, we note that in the results of Duranton *et al.* (2015), the sum of the coefficients on the factor misallocation terms are always close to unity. This is obviously consistent with establishments operating not far from constant returns. We also note that the factor shares obtained when estimating the empirical counterpart to equation (10) differ from the factor shares obtained when we estimate establishment productivity. As pointed by Duranton *et al.* (2015), land and buildings represent about 13% of the revenue of establishments but estimating equation (10) implies a factor share for land and buildings of 40 to 60%.

There are three possible reasons for that. The first that the price of land and buildings is at the margin much higher than what establishments pay on average. A second interpretation is that factor choices are not made simultaneously but sequentially with land and buildings being chosen first. Then labour and capital become functions of land and buildings and, unsurprisingly, the estimation of the empirical counterpart to equation (10) indicates a much greater importance of land and buildings than we observe in terms of expenditure. Alternatively, land may be a fundamentally important asset to obtain the external financing necessary to buy other fixed assets or to pay workers at the end of the month.

3.2 *Within and between misallocation: theory*

Our second decomposition is a between/within group decomposition. Before going any further recall that in Duranton *et al.* (2015), we compute indices of misallocation at the

district level. As mentioned above, computing the misallocation of, say, employment in each district separately yields a measure of the misallocation of workers within each district, taking as given the distribution of employment across districts. To be more precise, consider a population of establishments and a partition of this population into m groups denoted $g = 1, 2, \dots, m$. For instance, the population of establishments might be all establishments in our sample and each district may form a separate group. Alternatively, one may partition the population of establishments into the organised and unorganised sectors, different industries, etc.

By analogy with equation (4), which defines misallocation within group g , we can define misallocation for the entire population of establishments as

$$M = -(\Phi - \bar{\varphi}) = -n \operatorname{cov}(s_i, \varphi_i) = - \left(\sum_{i=1}^n s_i \varphi_i - \frac{1}{n} \sum_{i=1}^n \varphi_i \right), \quad (11)$$

where n is the total number of establishments. Using the fact that the share of an establishment in the population is equal to the share of that population in its group times the share of that group in the population, $s_i = s_{ig} s_g$, we can rewrite equation (11) as:

$$\begin{aligned} M &= - \left(\sum_g \sum_{i \in g} s_g s_{ig} \varphi_i - \frac{1}{n} \sum_g \sum_{i \in g} \varphi_i \right) \\ &= - \left[\sum_g s_g \left(-M_g + \frac{1}{n_g} \sum_{i \in g} \varphi_i \right) - \frac{1}{n} \sum_g \sum_{i \in g} \varphi_i \right], \end{aligned} \quad (12)$$

where the last simplification arises directly from the definition of M_g in equation (4). After using the definition of $\bar{\varphi}_g$ above and further simplifications, we can rewrite expression (12) as:

$$M = \sum_g s_g M_g - \sum_g \left(s_g - \frac{n_g}{n} \right) \bar{\varphi}_g. \quad (13)$$

Because $-\sum_g \left(s_g - \frac{n_g}{n} \right) = 0$ as the shares of both factors and establishments sum to unity, equation (13) can be finally written as:

$$M = \tilde{M} + M_\Delta \quad (14)$$

with $\tilde{M} \equiv \sum_g s_g M_g$ and $M_\Delta \equiv -\sum_g \left(s_g - \frac{n_g}{n} \right) (\bar{\varphi}_g - \bar{\varphi})$.

Hence, total misallocation for the population of establishments can be decomposed into the sum of two simple terms. The first, \tilde{M} , is within-group misallocation summed across groups, weighting them by their share s_g . The second term, M_{Δ} , is a measure of between-group misallocation. It is actually the between-group analogue of the covariance term used in equation (3). This makes strong intuitive sense: total misallocation is the sum of the misallocation of each group where each group is weighted by its factor share to which we add the misallocation across groups.

For instance, it is possible to imagine situations where more productive establishments employ more workers within each district, but that districts that host more productive establishments on average have access to substantially fewer workers than less productive districts. This would be a case of a low level of misallocation within districts but a high level of misallocation across districts. While most of our analysis is concerned with misallocation within districts, we pay some attention to the between component below. We also note that within- and between-district misallocations probably have very different root causes and most likely call for different policies.

3.3 Within and between misallocation: female- and male-owned establishments

Our first decomposition regards the differences between female- and male-owned businesses in the unorganised sector. We use the fact that the NSS reports the gender of business owners in the unorganised sector. As women suffer extensive discrimination in India, both as workers and as employers, it is important to assess, how much this discrimination affects misallocation in India.

The results are reported in table 1. Let us focus our discussion on a specific year, 2010. Although the exact numbers differ, the results for the other years follow very similar patterns. The misallocation index for output is -0.687. This is very close to the overall district mean for 2010 of -0.70. By the decomposition proposed in equation (14), -0.687 is the sum of within-group weighted misallocation of -0.605 and between group misallocation of -0.082. Hence, there is more output misallocation between groups rather

than within groups. Using the formula for \tilde{M} and M_{Δ} given above, we can compute that female owned establishments, which represent about 22% of the establishments produce only about 8% of output. This seems like an extremely low ratio of output to the number of establishments. This major imbalance may be at the root of much misallocation. However, the misallocation of output does not come from an abnormally low ratio of output to the number of establishments. Quite the opposite, this ratio is actually abnormally large.

To understand this, note that the difference in estimated productivity between male- and female-owned establishments documented in the last two columns of table 1 is about 0.57 log point. This is an extremely large productivity gap. Hence, should the two groups of establishment be similar in other respects, an extremely small share of output (and factors) for female-owned establishments would be desirable from an efficiency point of view. When a group of establishments is much less productive, efficiency requires this group to receive only a tiny share of factors.⁴

To insist, this last statement regards of course only efficiency and remains true only when the two groups of establishments are not too different in terms of misallocation within their group. This caveat regarding symmetry across groups is important. The fourth and fifth columns of table 1 report the misallocation of output within male- and female-owned establishments. They clearly show a greater amount of misallocation among male-owned establishments.

Female-owned establishments have access to less than 12% of employment, 10% of other fixed assets, and less than 9% of land and buildings. They manage to produce about 8% of output despite being immensely less productive. Given their much lower productivity, we would expect a set of representative female-owned establishments to produce only about 6.5% of total output. However, female-owned establishments produce 8% of total output because of less misallocation among them relative to male owned establishments.

Hence, the overall effect of female-owned establishments on the misallocation of output

⁴How tiny depends on the degree of differentiation between goods. See Melitz (2003) and subsequent literature for more on this.

is ambiguous. On the one hand, they receive too much factor given their extremely low productivity (or, perhaps more accurately, too many female workers may be stuck working for female-owned establishments).⁵ This contributes to more misallocation. On the other hand, misallocation is less among female-owned establishments, which contributes to less misallocation in the unorganised sector.

Two further results must bear notice in table 1. First, the lower level of output misallocation for female-owned establishments is the outcome of a lower level of factor misallocation. While for output, misallocation was worse across groups than within groups, the opposite is true for factors. For factors, female-owned establishments unambiguously contribute to less misallocation because (i) between-group misallocation is lower than within-group misallocation and (ii) there is less misallocation among female-owned establishments.

The reason why within-group misallocation is less severe for output is that even if establishments receive factors independently of their productivity, the most productive establishments will produce much more output than the less productive establishments. Here, despite extremely large productivity differences between female- and male-owned establishments, within-group heterogeneity is even greater.

3.4 Within and between misallocation: organised and unorganised sector

We repeat the same decomposition exercise but perform it on the organised and unorganised sectors instead of male- and female-owned establishments. The results are reported in table 2. Again, we focus our attention on 2010. The results for the other years of data exhibit similar patterns. Starting with the misallocation of output, we can note that, although the between-group component M_{Δ} is indicative of more misallocation than the within group components, \tilde{M} , they are both of roughly similar magnitude. This is in sharp contrast with the previous decomposition.

⁵This last point is certainly consistent with female-owned establishments being more labour intensive and having access to less in terms of land and buildings.

For factors of production, a different set of patterns holds, within-group misallocation is much worse than between-group misallocation. The within-group component is slightly negative for land and buildings and positive for employment and other fixed assets. Overall, the misallocation indices for factors are close to zero. This indicates a complete lack of correlation between factor use and productivity. On the other hand, factors are allocated much more efficiently between groups. Establishments in the organised sector, which are immensely more productive than establishments in the unorganised sector have access, on average to a much more quantity of factors of production.

Then, comparing misallocation within the organised sector with misallocation within the unorganised sector, we do not observe large differences between them. In 2010, there was slightly less misallocation in the organised sector for land and buildings but slightly more misallocation for employment and other fixed assets. These roughly similar numbers for factor misallocation are consistent with comparable misallocation indices for output across the two sectors. The differences in misallocation for previous years are sometimes larger but reflect again the lack of a clear ordering of the within-sector misallocation indices.

We also repeated the same exercise for each state and each district and found very similar results.

The conclusion regarding this decomposition is simple. The organised and unorganised sectors are roughly equally misallocated. The allocation of factors across the two sectors seems much more efficient as the more productive organised sector enjoys the use of disproportionately more factors.

3.5 Within and between misallocation: industries and districts

Our next step is to decompose misallocation within and between industries at the district level. To do so, we must make two minor changes relative to our previous decompositions. First, we decompose within each district our indices of misallocation into a within-industry term and a between-industry term. It would not be informative to report

numbers for misallocation of each district. Instead, we report means across districts. Hence, we should think of the results commented below as applying to an average district. Second, all our TFP estimations have so far followed the usual practice of normalising mean industry productivity to zero. This normalisation implies that the between term in the decomposition of misallocation is expected to be close to zero so that $M \approx \tilde{M}$.⁶ This is of course uninformative about misallocation across industries. The reason why mean industry TFP is usually normalised to zero is that we estimate different factor shares for different industries. As a result, it is unclear what an industry mean TFP really captures. We are not overly worried by this issue in our context because the factor shares are fairly constant across industries as discussed in Duranton *et al.* (2015). It is also the case that, when we compute misallocation directly at the district level without first aggregating within industries, we obtain misallocation indices that are very close to those we obtain when first aggregating within industries and then averaging across industries depending on their weight.

The results are reported in table 3. As in previous tables, the results are very similar across years. Hence, we can focus our discussion on 2010. First, because of the change of computation method for total factor productivity, the misallocation indices we obtain are not directly comparable with our earlier indices. Nonetheless the main descriptive features for total misallocation within districts are the same as previously. Namely: Misallocation is less important for output than for factors ; among factors, misallocation is higher for employment and land and buildings than for other fixed assets ; there is also a slight trend over time towards a worsening of misallocation.

Turning to the decomposition, the within and the between components are roughly of the same magnitude. Put slightly differently, misallocation appears to be as much an effect of factors being misallocated across establishments of heterogeneous productivity within industries as it is an effect of factors being misallocated across industries. Again

⁶It would be exactly zero when decomposing within and between industries at the national level. Patterns of Ricardian comparative advantage and sampling issues may make this term different from zero at the district level.

some caution is needed here because measurement problems could affect one term of the decomposition more than the other.

3.6 Within and between misallocation: country, states, and districts

We now turn to the decomposition of national misallocation into districts. As already argued, national misallocation may be about more productive establishments locally being unable to access factors and grow or about factors not being able (or willing) to move to more productive areas. These are two different phenomena, which arguably call for different policy responses.

The results for this geographic decomposition are reported in table 4. As with previous decompositions, the results are extremely stable over time so that we can focus our discussion on 2010 again. Many of the patterns already observed above still hold. For instance, there is less misallocation for output than for factors and factors are roughly equally misallocated.

The first striking new result is that national misallocation reported in the first column is often very close to the unweighted mean of district misallocation. Hence, to a large extent, the national picture about misallocation is a close reflection of what happens in an average district. Then, we can also note that the share-weighted average for misallocation across districts, \tilde{M} , is typically higher than the unweighted mean. Larger districts, where output is higher and factors more abundant, are also more misallocated districts. As shown by column 5, there is a lot of variation in misallocation across districts.

At the same time we also observe that the between-district term, M_{Δ} , is also negative and of about the same magnitude as the difference between the weighted and unweighted mean district misallocation. This explains why national misallocation is about the same as district misallocation. The negative sign of M_{Δ} suggests that more productive districts produce more output and receive more factors of production per establishment. Because larger districts with more factors and more establishments are also often more productive

districts, we end up in the following situation.⁷ Larger and more productive districts make national misallocation worse because of their worse misallocation. At the same time, they have more factors which reduces national misallocation. The two effects roughly offset each other so that national misallocation is not very different from misallocation in an average district.

Finally, we can also see that the between-district misallocation term, M_{Δ} is much higher than the within-district misallocation term, \tilde{M} . This is despite large differences in TFP across districts, as shown by the last column of table 4, which reports the standard deviation of district TFP. These values of between-district misallocation close to zero occur despite large differences across districts in productivity. They are suggestive of a lot of misallocation of factors of production across districts.

In table 5, we report results for a similar decomposition but, this time, for districts within states. The reported results are averages across states. They show very similar patterns as the previous decomposition of districts within the country. Mean district misallocation within states is very close to mean state misallocation. Again, larger districts appear more misallocated so that the weighted mean of district misallocation within states (the cross-state mean of \tilde{M}) is higher than its unweighted mean. It is also the case that between-district misallocation within states is high.

Finally table 6 reports results for the decomposition of national misallocation within and between states. The results are highly consistent with those of the previous two decompositions and, if anything, even more marked. The between-state misallocation term is close to zero suggesting that establishments in more productive states do not receive on average more inputs.

Taking all these results together, two major conclusions emerge. First, the misallocation picture remains the same whether we look at the country, state, or district level. This is an important message, which suggests that much can be learnt from the cross-section of districts. Second, there is a lot of misallocation between districts within states and between

⁷This is confirmed by column 6 which shows that (unweighted) mean district TFP is negative whereas the national mean is normalised to zero.

states. This is consistent with the perception that India suffers from a major problem regarding factor mobility(see for instance Munshi and Rosenzweig, 2016). Importantly, the results appear to be the same for a mostly immobile factor such as land and buildings as for supposedly more mobile factors such as employment or other fixed assets.⁸

4. An exploration of the service sector

In this section we duplicate the analysis of Duranton *et al.* (2015) for the service sector. This is a useful exercise for a number of reasons:

- Can we confirm that factor misallocation affects output misallocation?
- Can we confirm the importance of factor misallocation on output per worker?
- Did policies affect factor misallocation?
- Is land as important for services as it is for manufacturing?

4.1 Data and descriptive statistics

Beginning with the 57th round during July 2001 to June 2002, the NSSO conducted a survey of the unorganized enterprises belonging to the service sector and this survey was repeated as part of the 63rd round of National Sample Survey (NSS) during July 2006 June 2007. The 57th round covered broadly all unorganised service sector enterprises engaged in the activities of hotels and restaurants; transport, storage and communication; real estate, renting and business activities; education; health and social work and other community, social and personal service activities. The 63rd round additionally covered financial intermediation services which was not so in the 57th round while specific sectors such as non-mechanised transport activities related to transport via railways and activities of business, employers and professional organizations were covered in 57th round but excluded from coverage in 63rd round. Neither survey covered the service sector enterprises

⁸While land is immobile, this is not the case for buildings before their location is decided. We must also keep in mind that we are talking about manufacturing land which represents only a small proportion of total land. Its supply should be arguably somewhat flexible unlike the total supply of land. As an additional point, note also that the immobility of land might be driving the immobility of the other factors. While this is true to some extent, it is hard to believe that land and other factors are perfect complements.

pursuing the activities of wholesale and retail trade, repair of motor vehicles, motorcycles and personal and household goods; public administration and defence; private households with employed persons and extra-territorial organizations and bodies. As in the case of the NSSO surveys for manufacturing establishments, the sample stratification in services is also includes both the district level and the two-digit NIC sectors.⁹

The survey covered the whole of the Indian Union except (i) Leh (Ladakh), Kargil, Punch and Rajauri districts of Jammu & Kashmir, (ii) interior villages situated beyond 5 km of a bus route in Nagaland, (iii) villages of Andaman and Nicobar Islands, which remain inaccessible throughout the year. Thus the corresponding State/UT level estimates and the all-India results presented in this report related to the areas covered under survey.

As in the case of manufacturing surveys, the services counterpart of the NSSO survey collects analogous establishment-level information on the output, inputs (raw materials and other inputs), fixed assets, value of land and buildings, employment, energy consumption and so on. The sample stratification is also similar to that of the NSSO.

Altogether a total of 190,142 service sector enterprises considering both list frame and area frame were surveyed in the 63rd round while the 57th round generated 359,702 establishment level observations. Thus, we have a total of 549,844 observations across the two years. We note that industries with two-digit National classification code 61 (Inland, sea and coastal water transport), 73 (research on natural sciences, engineering, social sciences and humanities) and 90 (sanitation services) have fewer than 400 observations each year and hence not suitable for any industry level computations, such as total factor productivity estimations. Thus, we drop these observations, and are left with 359,050 observations in 2000 and 189,584 in 2005, giving us a total of 548,634. For our calculation of productivity and misallocation metrics, we need to further clean up the data by dropping observations belonging to unknown district names, and small and conflict states. These include Andaman and Nicobar Islands, Dadra & Nagar Haveli, Daman & Diu, Jammu & Kashmir, Tripura, Manipur, Meghalaya, Mizoram, Nagaland and Assam. The final

⁹Furthermore, as the NIC definitions have changed over time, we make them consistent using concordances that come with the data.

sample that we work with for productivity and misallocation metrics consists of 490,948 observations for both years. Finally, we drop observations with negative value added, missing raw materials value and missing values of fixed assets. Thus, we are left with 464,285 observations in total, with 308,475 corresponding to the year 2000 and 155,810 from 2005. This leaves us with over 380 districts each year. See table 7 for some descriptive statistics.

To estimate total factor productivity, our preferred specification regresses establishment value added on employment and total fixed assets with OLS. We check our results with an alternative specification where we use three factors of production to distinguish between land and buildings and other fixed assets. This second specification is closer to the spirit of what we do below. Nonetheless, we do not use it as our baseline because breaking down capital into different components will introduce more measurement error and may lead to less precise productivity estimates. In practice, taking one or the other estimate of TFP makes minimal differences as the two are highly correlated as we shall see below.

In future work, we should be able to use at least one more year of data and used more refined productivity estimates as in Duranton *et al.* (2015).

4.2 Results for the determinants of misallocation

We start by estimating regression (6) for services. The results are reported in table 8. The same regressions are estimated in both panels. The main difference is that the regressions in panel B are weighted by district employment whereas those in panel A are unweighted. Column 1 regresses the misallocation of output per worker for services in Indian districts on corresponding measures of misallocation for employment, land and buildings and other fixed assets. The estimated coefficient on employment misallocation is high at 0.80 and extremely significant. The coefficient on misallocation of other fixed assets is much lower at 0.14 but nonetheless significant. The coefficient on the misallocation of land and buildings is of the same magnitude as that on fixed assets at 0.13 but insignificant. The coefficient on employment misallocation in panel B where we use district

employment to weight observations is slightly lower than the corresponding unweighted coefficient. The coefficient on the misallocation of other fixed assets is virtually unchanged while the coefficient on the misallocation of land and buildings is higher at 0.20 and significant at 5%.

In column 2, we consider all forms of capital together. The coefficient on employment misallocation is marginally higher while that on all fixed assets approaches the sum of the coefficients of its two components in the previous columns. In column 3, we add district fixed effects to the regression of column 1. All the estimated coefficients decrease but only slightly so. This leads to a loss of significance of land and building and other fixed assets. The coefficient on employment misallocation remains highly significant. In column 4, we repeat again our baseline estimation of column 1 but measure output per worker through a measure of gross revenue per worker instead of value added and find similar results. In column 5, we use a measure of total factor productivity estimated with three production factors instead of two. The differences with column 1 are small. The coefficient on the misallocation of employment increases while those on the other factors decrease.

Finally, columns 6 and 7 use measures of misallocation computed using the covariance between output or factor shares with output per worker as a measure of productivity. These two columns yield substantially different results with much higher coefficients on the misallocation of land and buildings and other fixed assets. On the other hand, the coefficient on the misallocation of labour is now insignificant with point estimates close to zero.

To understand the results of these last two columns and why they differ so much from those reported in the previous column, the first point to note is that output per worker and total factor productivity are less highly correlated than one might have thought. The correlation between output per worker at the establishment level and our preferred measure of OSL TFP is 0.35. At the same time, the correlation between our preferred measure of TFP with two factors and one estimated with three factors of production (distinguishing between land and building and other fixed assets) is above 0.90. Hence,

even though services are highly labour intensive, other factors still matter. Put slightly differently, differences in output per worker will measure differences in capital intensity more than differences in productivity. This will be especially true when employment is poorly allocated across establishments. Hence the covariance between employment and output per worker will measure essentially the same thing as the covariance between land and buildings (or other fixed assets) and output per worker, only less well. As a result when both types of covariances are used in the same regression, that between employment and output per worker (i.e., employment misallocation) will have little to no explanatory power.

The first key conclusion we can draw from table 8 is that the sum of the coefficients on factor misallocation is close to one unless we measure establishment productivity with output per worker, in which case it ranges between 0.75 and one. This finding mirrors our result in Duranton *et al.* (2015) for manufacturing. As we show in section 3.1, under a Cobb-Douglas production function we can decompose the misallocation of output among a group of establishments into the sum of their factor misallocations each weighted by its share in the production function. Hence, under constant returns to scale, we expect the sum of the misallocation coefficients to be close to one in regression (6). This provides a useful validation of our misallocation indices and a check on the quality of the data.

The second key conclusion we draw from table 8 is that the misallocation of employment appears to play a key role in determining output misallocation. This is consistent with the high levels of labour intensity of most service industries. This result is also very much in contrast with the result that, in manufacturing, the key driver of the misallocation of output is the misallocation of land and buildings.

A number of further points are also worth noting. First, the coefficient on the misallocation of land and buildings shows a greater tendency to be significant when the regressions weight districts by their initial employment level. This finding mirrors similar findings in Duranton *et al.* (2015) and is consistent with the notion that the misallocation of land and buildings matters more in denser districts where the pressure on land is perhaps

greater. There is also a potential worry that measures of productivity for services may be extremely noisy, more so than for manufacturing. The fact that in columns 1-5, the sum of misallocation coefficients is close to one is reassuring in this respect. Another validation comes from the fairly high levels of R^2 especially in the weighted regressions. In these latter regressions for services, the R^2 are roughly similar to those obtained for manufacturing.

In results not reported here, we also experimented with a more dynamic approach to the relationship between output and factor misallocation by regressing changes in output misallocation over time on the initial level of output misallocation and initial factor misallocation. Because misallocation is not well measured, the change in output misallocation over time is strongly negatively correlated with its initial level. In Duranton *et al.* (2015), we found some evidence that for manufacturing the initial misallocation of land and buildings breeds subsequent output misallocation in denser districts. In services, there is modest evidence that something similar happens with the initial misallocation of employment that affects the subsequent misallocation of output.

In tables 9 and 10, we also briefly investigate the policy determinants of misallocation in services across Indian districts. As in Duranton *et al.* (2015), we estimate a version of regression (5) where we use changes in the planning regulations that affected major Indian cities. The Parliament of India enacted the Urban Land (Ceiling and Regulation) Act (ULCRA) in 1976. Its main objective was to limit the concentration of urban land by imposing ceiling limits for holdings of vacant land, prohibited many transfers of land and buildings, and restricted building construction in 64 of the largest urban agglomerations (central cities and their suburbs). For almost a quarter century, ULCRA practically halted legal development of land by the private sector in urban areas unless exemptions were obtained (Srinivas, 1991, Sridhar, 2010). The regulation and market constraints reduced the incentives of landholders to invest in building construction. Thus, a large proportion of establishments were both land and building constrained by way of ULCRA.

The Repeal Act in 1999 gave rights to state governments of India to repeal ULCRA. As

argued in Duranton *et al.* (2015), this reform was mostly unanticipated. A number of states and UTS had repealed ULCRA by 2003, including Delhi, Gujarat, Haryana, Karnataka, Madhya Pradesh, Orissa, Punjab, Rajasthan, and Uttar Pradesh. By contrast, Andhra Pradesh, Assam, Bihar, Maharashtra, and West Bengal kept ULCRA effective until 2008.

To assess the effects of the repeal of ULCRA on misallocation, we estimate a series of regressions in the spirit of regression (5) where we consider the district-level change in misallocation for services from 2000 to 2005 as the dependent variable. Our key explanatory variable is an indicator variable for states that repealed ULCRA early, as listed above.

Unlike for manufacturing, we find very little effects of the repeal of ULCRA on output or land and building misallocation in table 9. In all cases the coefficient on the repeal of ULCRA is positive, indicating a worsening of misallocation. However this coefficient is significant in only three cases. This constitutes modest evidence of a perverse effect of the repeal of ULCRA on misallocation. For manufacturing, the results of Duranton *et al.* (2015) indicate a strong, negative, significant effect of the repeal of ULCRA on misallocation. It may be that ULCRA helped land intensive manufacturing establishment expand, which reduced misallocation in manufacturing. Alternatively, the repeal of ULCRA may have made it easier for unproductive manufacturing establishments to convert their land and sell it. Their exit may have reduced misallocation in manufacturing. Many entrants in the service sector using this newly available land may not have been the most productive establishments within services either because these were very young establishments for which measured productivity is often low or because establishments that can buy or lease land may be less productive large incumbents.¹⁰

We confirm this perhaps surprising finding by looking at the effects of changes in stamp duties. Stamp duties are taxes are collected whenever a real property is transacted. High stamp duties impose high compliance costs on taxpayers and lead to widespread avoidance through under-reporting. This, in turn, adversely affects the possibility of using land as collateral for construction financing. High stamp duties also discourage

¹⁰It may also be that the adjustment towards a less misallocation takes longer and that these policy changes led to initially more misallocation. See below for further discussion of such effects.

land transactions, and, as a consequence, reduce the supply of land on the market.

Although stamp duties are high in India by international standards, there is a lot of variation across states and time. Table 10 uses a difference-in-difference estimation similar to Table 9 to consider the relationship between changes in stamp duties at the state level and changes in local misallocation in services. We consider changes in misallocation from 2000 to 2005 as the outcome variable and changes in stamp duties over the same period as the core explanatory variable.

Table 10 reports that lower stamp duties are associated with more misallocation. While this finding is not particularly strong, it is clearly in sharp contrast with the opposite finding for manufacturing in Duranton *et al.* (2015). This suggests again that policy changes that reduce frictions in the land market reduce misallocation in the manufacturing sector but they appear to mildly increase misallocation in services.

4.3 Results for output per worker

To finish with services, we turn to regression (7) and estimate the effect of factor misallocation on output per worker. The results are reported in table 11. Panel A reports results for a pooled cross-section of districts. Panel B report results for the same set of districts but weights them by their initial employment. Because the results are essentially the same across both panels, we will only discuss the results from panel A.

Column 1 regresses the misallocation of output in services for 2000 and 2005 on the misallocation of land and building, the misallocation of other fixed assets, and the misallocation of employment. The coefficient on the misallocation of employment is negative, large in magnitude, and highly significant. More misallocation of employment is associated with less output per worker. The coefficient of -0.88 indicates that a 0.1 increase in index of employment misallocation is associated with an about 9% decrease in output per worker. Alternatively, a one standard deviation increase (0.2) in the misallocation of employment is associated with a decline of 16% of output per worker. The coefficient on the misallocation of land and buildings and that of other fixed assets are both positive and

significant, albeit of much smaller magnitude. Because these coefficients are strongly negative when estimated alone and because our misallocation indices are highly correlated across factors, this regression is likely to suffer from multicollinearity.¹¹

Column 2 considers misallocation for all fixed assets and yields essentially similar results. Adding district fixed effects in column 3 makes the coefficient on employment misallocation insignificant. We need to remain cautious when interpreting this result since our panel for services is extremely short. It is likely that we miss the statistical power to estimate this regression properly. Considering an alternate measure of TFP estimated using three factors of production instead of two in column 4 makes little difference relative to our baseline estimation in column 1. Using yet another measure of productivity – output per worker – to compute misallocation in columns 5 and 6 leads to roughly similar results for land and buildings and for other fixed assets. The coefficients for employment misallocation are lower.¹²

These results are again in contrast with those of Duranton *et al.* (2015) for manufacturing. For services, the key measure of misallocation that explains output per worker the misallocation of employment whereas for manufacturing it was the misallocation of land and buildings.

To conclude on services, we can return to the questions raised at the beginning of this section and provide answers to them.

- Can we confirm that factor misallocation affects output misallocation?

Yes. Although the relative importance of factors differs in services relative to manufacturing, we find strong evidence that the misallocation of factors has a strong effect on the misallocation of output. In line with the factor decomposition of the misallocation of output proposed above, we find that the sum of the estimated coefficients is close to one. This is an important validation of our approach.

- Can we confirm the importance of factor misallocation on output per worker?

¹¹For the indices used in column 1, the pairwise correlations between the misallocation of employment and either land and building or other fixed assets is about 0.60.

¹²As per the argument made above, empirically the covariance between employment and output per worker will not constitute a good measure of the covariance between productivity and output per worker.

Yes. Again, the relative importance of factors differs in services relative to manufacturing but we do find a strong effect of misallocation on output per worker. Overall we find effects that are similar to those found for manufacturing.

- Is land as important for services as it is for manufacturing?

No. While the misallocation of land and buildings plays a major role in manufacturing, it seems to play at best a minor role in services. On the other hand, in services it is the misallocation of employment that appears to be the main determinant of output misallocation.

- Did policies affect factor misallocation?

Yes. Our results are nonetheless fairly subtle because we examine policies that primarily affect the land market. The functioning of the land market is fundamental for manufacturing and, perhaps, secondary for services. In light of this, we find that policies that were found to increase misallocation in manufacturing had, if anything, the opposite effect on services.

To sum up, the two key takeaways from our analysis of the service sector is that factor misallocation affects output in services in essentially the same way as it does in manufacturing but the crucial factor in services is labour instead of land for manufacturing. Since distortions are arguably worse for the land market than for the labour market, this raises the possibility that this may be a key determinant of India's success in services relative to manufacturing.

5. Robustness: effects of policies on misallocation

5.1 Background on policy changes

In Duranton *et al.* (2015), we explored the consequences on factor and output misallocation in Indian districts of the repeal of ULCRA and stamp duty changes. There is some evidence that lower stamp duties and the repeal of ULCRA both led to less misallocation in manufacturing. As just showed above, the results are different for services. There are two potential worries with this analysis. First, these policy changes may have been determined

simultaneously with changes in misallocation. Although a good case can be made that the repeal of ULCRA came as a surprise, matters may be less clear for changes in stamp duty taxation. The second worry is that these policies are particular. We expect them to affect mostly the property markets. It is unclear whether our findings for these two policies can be generalised to policies affecting other factors of production.

With this in mind, we now turn to a broader set of policies affecting labour markets, land markets, entry into manufacturing, foreign investment, and international trade.

The regulation of the land and labour markets in India is made at the state level. There is a lot of cross-sectional variation between states with, perhaps at one extreme, a state like Gujarat where the outlook is pro-market, and at the other, West Bengal, which was historically ruled by communists-led coalitions. There have also been many changes over the years. These changes were recorded by Besley and Burgess (2000) for the land market and Besley and Burgess (2004) for the labour markets. These data series were subsequently expanded to 1997 by Aghion *et al.* (2008).

The coding of labour market changes by Besley and Burgess is straightforward for our purpose. Any change in labour market regulations in a state for any given year is assessed to be either pro-worker or pro-employer. We expect pro-worker changes to create more frictions on the labour market and increase misallocation. We expect pro-employer changes to work in the opposite direction.

Matters are more complex for the land reforms. First, in large part they concerned rural land since Besley and Burgess (2000) find much larger effects of these reforms in rural areas than in urban areas. These reforms may have affected misallocation in manufacturing through the location choices of manufacturing establishments and may be part of the explanation behind the decentralisation of manufacturing in India (Ghani, Goswami, and Kerr, 2012). Land reforms are also more heterogeneous and their effects on the functioning of land markets less obvious. A first group of reforms concerned the regulation of tenancy. These reforms attempted to give clearer rights to tenants. While greater rights for tenants can lead landowners to hold on to parcels that are inefficiently

used, they may also provide greater incentives to tenants to invest more in their parcels. A second group of reforms attempted to abolish intermediaries. These reforms may have improved the efficiency of land markets. A third group of reforms attempted to consolidate land holdings, which may also have improved efficiency. Finally, like with urban land, some reforms attempted to impose some ceilings on land holdings with a view to redistribute land. These reforms may have worsened frictions on the land market. It is important to keep in mind Besley and Burgess's (2000) conclusions. Overall, land reforms in India have had positive effects in terms of poverty reduction and agricultural wages. However, in many instances agricultural output was reduced. This pattern is consistent the conversion of agricultural land to manufacturing use. Besley and Burgess (2000) also find that most of the effects of land reforms can be traced back to changes in tenancy regulation and to the abolition of intermediaries.

Next we turn to industry delicensing. After independence, Indian manufacturing industries were subjected to a strict licencing system. 'Raj licences' were an essential tool for the planning of the Indian economy by the government. Entry, expansions, significant changes in capacity, relocations, and even product changes were all governed by a strict system of permit by a government willing to fine-tune the development of manufacturing in India. A first wave of reforms occurred after the rise to power of Rajiv Gandhi in the mid 1980s, following his mother's assassination. These reforms were largely unexpected. A second wave of reforms also occurred in the early 1990s when Congress returned to power following the assassination of Rajiv Gandhi and a balance of payment crisis put pressure on the incoming government to liberalise. Industrial licencing had effectively disappeared in a large majority of industries by the mid 1990s.

Together with delicensing, the Indian government also reduced the barriers to foreign direct investment and lowered tariffs. For delicensing, foreign direct investment, and tariffs, we follow Aghion *et al.* (2008).

5.2 *Effects of policies on misallocation*

To assess the effects of these reforms, we build a panel of industries across states and compute changes in output misallocation between 1989 and 2000. This is our dependent variables in the regressions reported in table 12. Note that relative to our analysis of services in section 4 or to the results presented in Duranton *et al.* (2015), we work with different units, industries within states instead of an aggregate of industries within districts. Below, we assess to what extent this different level of analysis affects our results.

Our main explanatory variables are the reforms described above, which we aggregate over 1985-1997. Hence, our estimations regress changes in misallocation between 1989 and 2000 on institutional and policy changes between 1985 and 1997. We also consider longer lags for changes in misallocation below. Because changes in misallocation are often noisy and because the initial level of misallocation may be correlated with what triggered some of the reforms, we also control for the initial level of misallocation in our regressions.

From the regressions reported in table 12, we can draw a number of conclusions regarding the effects of institutional and policy changes. The first one regards the effects of labour reforms. Stricter pro-worker regulations led to a worse misallocation. This result is robust across most specifications. It is only when we break down our sample and distinguish between the organised and the unorganised sector that the effect of labour reforms become insignificant. This is perhaps unsurprising since labour reforms are thought to have pushed many establishments into the unorganised (informal) sector (Besley and Burgess, 2004).¹³ More generally, this negative effect of pro-worker labour reforms is fully consistent with the conclusion of Besley and Burgess (2004) who find that these reforms were generally harmful to industrial development in India.

The second strong result that emerges from table 12 regards land reforms. These reforms led to less misallocation in manufacturing. Like with labour reform, it is only when we look within the organised sector or within the unorganised sector that the effects are insignificant. As argued above, the net effect of land reforms is in theory ambiguous

¹³See Duranton, Gobillon, and Overman (2005) for a more detailed discussion of the possible pitfalls associated with looking at misallocation over only one part of the establishment size distribution.

since some particular reforms were expected to worsen misallocation, while others were expected to improve misallocation. Empirically, the positive effects appear to dominate. We note that this conclusion is consistent with that of Besley and Burgess (2000) who find that land reforms improved the plight of agricultural workers in India, even though agricultural output declined. It would be interesting to assess how land reforms affected the location of economic activity in India to gain further insight about the positive effects of land reforms on misallocation. This is, however, beyond our scope here.

The third and fourth results are perhaps more surprising. We find that higher tariffs are associated with less misallocation while FDI liberalisation is associated with more misallocation. These results may seem surprising as we might have expected entry by foreign establishments and greater import competition to have improved misallocation, not worsened it. These effects are moderately large. Using the coefficients of column 1 of table 12, tariff changes led to an about 0.1 increase in misallocation when valued at the mean whereas FDI liberalisation in an industry increased misallocation by 0.065.

When duplicating these regressions over a longer time period for the change in misallocation, an interesting pattern emerges. When looking at changes in misallocation over 1989-2005 instead of 1989-2000, the 'perverse' findings essentially disappear for FDI and are much attenuated for trade liberalisation. When looking at changes in misallocation over 1989-2010, the reversal gets even stronger. The results are presented in table 13. The effects of trade liberalisation on misallocation become insignificant and those for FDI are now strongly negative. Hence, after a longer time period, FDI liberalisation is associated with a strong decline in misallocation. Because many other things may have happened in the intervening 2000-2010 period, we must of course remain cautious when interpreting this finding. Interestingly perhaps, the effects of labour and land reforms are mostly unchanged when we take 2010 as the end of the study period instead of 2000.

Finally, the last result regards delicensing. In table 12, delicensing is associated with a modest and insignificant negative effect on misallocation. As shown in table 13, by 2010

these effects are much stronger and highly significant.¹⁴

These results are consistent with two well documented patterns. First, reforms like trade liberalisation require some time before everything fully adjusts. For instance, Trefler (2004) shows that the US-Canada free trade agreement led first to losses in Canadian manufacturing before the gains eventually materialised. Initially many establishments had to exit and large numbers of manufacturing jobs disappeared. It is only after a long period that winning establishments managed to offset these job losses, productivity was significantly up, and consumers gained through lower prices. While this adjustment may have taken up to ten years in Canada, it may not be surprising that it took even longer in India where factor markets are much less flexible.

This explanation does not, however, explain why the initial effect of these reforms was to make factor misallocation worse. The simplest models of trade liberalisation with heterogeneous establishments (e.g., Melitz, 2003) suggest that the least productive establishments (arguably responsible for most misallocation) should exit first. This need not be the case. As shown by Holmes and Stevens (2014) in the US case, the surge in Chinese imports over the last 20 years led, in many industries, to the exit of the bigger establishments. This was because these bigger establishments were much more exposed to import competition from China, while smaller establishments catering to more specific market segments remained in business. Put differently, mainstream furniture producers were, for most of them, wiped out by Chinese imports, while speciality furniture producers were much less affected, even though some of them are poorly productive workshops in rural parts of America.

In results not reported here, we also conducted a series of robustness checks where we started the reform period either earlier (1981) or later (1989) and also estimated the same regressions as in tables 12 and 13 but without controlling for initial misallocation. The results for these alternative specifications are consistent with those reported here.

¹⁴This is not true however when we examine only the organised or the unorganised sector. As argued above, much caution is needed to interpret these regressions because we look at misallocation only over one part of the size distribution of establishments.

We draw two important conclusions from this analysis so far. First, the results of our work on the repeal of ULCRA and on stamp-duty taxation extend to other, broader policies affecting labour, land, international trade and investment, and the regulations of industry. This provides a further validation of the measures of misallocation we developed. This also gives support to the idea that policies can have large effects on misallocation. Second, some policies may take very long to show their long-run effects. Because factor markets in India are subject to considerable frictions, delicensing or trade or FDI liberalisation may lead first to a worsening of misallocation before it improves.

5.3 Robustness check: effects of factor misallocation on output misallocation for industries and states

We now estimate again regression (6) using the same observations as above: industries by state. More precisely, we regress the misallocation of output on the misallocation of the different factors of production.

The results are reported in table 14. In the baseline estimation of column 1, we find that in panel A the coefficient on the misallocation of employment is equal to 0.60 while the coefficients for the misallocation of land and buildings and for the misallocation of other fixed assets are equal to 0.16. All three coefficients are highly significant. Next, we consider different groupings of factors, a different way to measure establishment output (revenue instead of value added), and add fixed effects for industries and / or states. The results are essentially unchanged.

Estimating the same regressions by weighting observations by initial employment leads to equally strong results in panel B of table 14. The only difference is that the coefficient on the misallocation of employment and that on the misallocation of land and buildings are now about equally large.

Importantly, the coefficients on factor misallocation usually sum to between 0.9 and 1.0. This is close to the theoretical prediction of 1 discussed above. This result provides yet another validation for this prediction. Again, this lends credence to both our approach

and the data we use. Relative to Duranton *et al.* (2015) who work at the level of districts, using industries and states leads to a lesser importance of the misallocation of land and buildings and a greater importance of the misallocation of employment. This difference should be kept into perspective nonetheless because the relative size of the coefficients obtained here are somewhat sensitive to the exact weighting scheme used to estimate the regressions. We also use the data at a different degree of aggregation. The misallocation of land and buildings may be more important when we look at a finer degree of spatial resolution, districts instead of states.

5.4 Robustness check: effects of factor misallocation on output per worker for industries and states

Turning to regression (7), we now assess the effect of factor misallocation on output per worker. In column 1 of table 15, we regress output per worker on misallocation for employment, land and buildings, and other fixed assets. The coefficient for the misallocation of employment is negative and highly significant. The coefficient on the misallocation of land and buildings is also negative and significant but smaller by nearly 50%. The coefficient on other fixed assets is instead positive and highly significant. Although of opposite sign, its magnitude is about the same as that on the misallocation of land and buildings. As can be seen for the other columns of the same table, these patterns are extremely robust except for the significance of misallocation of other fixed assets. When imposing both industry and state fixed effects, the coefficient on employment misallocation remains at -0.3 while that on the misallocation of land and buildings remains at -0.2. It is only when we look at the organised sector separately that the patterns are somewhat different with some differences across the two sectors. For the unorganised sectors, the effects of employment and land and buildings misallocation are stronger while those of other fixed assets misallocation are positive and highly significant.

A first explanation for these slightly conflicting results and the estimation of positive coefficients is the presence of multicollinearity problems. The correlation between the

misallocation of land and buildings and the misallocation of other fixed assets is 0.72. The correlation between the misallocation of land and buildings and the misallocation of employment is 0.63. Finally, the correlation between the misallocation of employment and the misallocation of other fixed assets is 0.58. Because of these high pairwise correlations, it is difficult to separately identify the effects of each factor misallocation.

To minimize the importance of multicollinearity, table 16 essentially mirrors table 15 but ignores the misallocation of other fixed assets. Looking at column 5 which includes both industry and state fixed effects, the coefficient on the misallocation of employment is about -0.3 whereas that on the misallocation of land and buildings is about -0.2, which is very close to the coefficients obtained in the previous table.

While we no longer estimate positive coefficients when ignoring other fixed assets, the estimated effects differ somewhat from those in Duranton *et al.* (2015) at the district level. For states and industries, the misallocation of land and buildings appears to play less of a role while that of employment plays a bigger role relative to estimations performed across industries at the sector level.¹⁵ A part of the explanation here is that the misallocation of labour worsens as more aggregate units of analysis are considered due to the extremely low mobility of labour in India Munshi and Rosenzweig (2016).

6. Robustness: towards asserting causality and further checks

6.1 Causality issues in the misallocation on misallocation regressions

The analysis proposed in Duranton *et al.* (2015) was mostly descriptive in spirit and made no attempt at relying on a plausibly exogenous source of variation to establish a chain of causal events except when looking at the policy determinants of misallocation. Regressions (6) and (7) were estimated using ordinary least squares. Let us first focus on

¹⁵We also find that when weighting the regressions by initial employment, the levels of significance of the estimated misallocation coefficients drops. This is most likely because the manufacturing sector is dominated by a few large industries.

equation (6) which regresses output misallocation on the misallocation of employment, land and buildings, and other fixed assets.

A first possible worry is that some local 'constraint' may lead a bunch of more productive establishments to produce less than they otherwise would. That would be a case of the misallocation of output driving the misallocation of factors. Possible examples of such constraints include local permits, discrimination of consumers against certain establishments, etc. As a result, these establishments will choose to employ less of each factor.

Because our results when estimating regression (6) are the same in cross-section and in the within dimension, such 'constraints' need to be thought of as shocks, not permanent features that prevent more productive establishments from expanding. But then establishments should react by adjusting first more flexible factors of production, labour, or perhaps, given the rigidities of the Indian labour market, other fixed factors. So, the misallocation of output should breed the misallocation of the more flexible factors. Instead we observe, the opposite. The strongest association is between the misallocation of output and the misallocation of land and buildings.

Another route to explore is to instrument factor misallocation. As argued above, finding appropriate instruments for factor misallocation is challenging. A policy may affect the misallocation of one factor but it may also directly impose unobserved constraints on production. Instead, we instrument factor misallocation in a given period by misallocation of the same factor at the previous period, that is about 5 years before. For this instrumenting strategy to be valid, we need past factor misallocation to cause current factor misallocation. This can be assessed empirically. We can confirm this is the case, at least in some specifications. We also require past factor misallocation to be correlated with current output misallocation only through current factor misallocation or through one of the controls included in the regression. While lags in the production process or anticipated factor adjustments may invalidate this strategy, using such instruments increases the distance between the variation to be explained for contemporary output and the variation used to explain it.

The results are reported in table 17. The main issue is that the instruments are often weak which leads to noisy and insignificant estimates. It is only in columns 2 where only two factors of production (employment and all fixed assets) and 4 that the instruments are strong. The results in column 4 remain noisy. We note however that the IV results of column 2 are very close to their corresponding OLS estimation in Duranton *et al.* (2015). The results of columns 1 and 3 are also close to their corresponding OLS estimates despite larger standard errors.

Overall, three elements support the notion that the results of regression (6) are causal. First, the sum of the estimated OLS coefficients is in line with the prediction of our model where factor misallocation breeds output misallocation. Second, should output and factor misallocations be simultaneously determined, we would expect a stronger correlation of output misallocation with the factors that are easier to adjust. The opposite occurs in the data. Finally, a tentative IV strategy never refutes our initial findings and in a few cases closely matches them.

6.2 Causality issues in the output per worker on misallocation regressions

We now turn to a similar instrumenting strategy for regression (7) where we assess the effect of factor misallocation on output per worker. Again, we worry about the simultaneity of misallocation and output per worker. The difficulty with findings instruments for misallocation is that determinants of factor or output misallocation may also affect output per worker through a number of different channels. That would be the case for instance with the policies that we have explored above. They will affect output per worker through their effects on misallocation. However, they may also affect output per worker through a variety of other channels or perhaps even directly. A similar argument will hold for any contextual variable that affects misallocation. Such variable may also have a direct effect on productivity or an indirect effect through a number of alternative channels. This invalidates the use of policy and contextual variables as instruments.

Instead, we use past misallocation to instrument for current misallocation. While this

instrument might fail because past misallocation may be correlated with contemporaneous determinants of output per worker, this bias should remain small when we control for permanent characteristics of districts through district fixed effects.

The main challenge is that regression (7) contains three potentially endogenous explanatory variables. They are fairly highly correlated among themselves and so are their lagged values. As a result, iv estimates with three instrumented measures of misallocation are unstable. Instead, we use measures of misallocation only one at a time, focusing mainly on the misallocation of output.

The results are reported in table 18. In OLS, the estimated coefficient on the misallocation of output is -0.74. Instrumenting it with its past value raises its magnitude slightly to -0.94 in column 1. Adding district fixed effects lowers it to -0.46. Weighting by initial employment raises it again to -1.14 while computing misallocation directly across all industries without going through an intermediate stage of industry aggregation leads to a coefficient of -0.55. Using instead the misallocation of employment or that of land and buildings leads to very similar point estimates. Because of larger standard errors, the coefficients when including district fixed effects are insignificant when using factor misallocation instead of output misallocation as explanatory variable.

Even though, there is some variation in the estimated effects of misallocation across specifications, they remain in the -0.5 to -1 range which is the same as the one we obtain when estimating these regressions using OLS.

We experiment with another instrument that we construct using the tendencies of different industries to be misallocated. More specifically, recall that before computing misallocation at the district level, we first compute it for each district and industry. From that intermediate output, we can estimate the tendency of each industry to be misallocated using industry fixed effects. For each district and industry, we can then multiply the share of each industry by the tendency for this industry to be misallocated and sum across all industries in the district. For each district, that gives us an expected misallocation index based on the local composition of economic activity and the national tendency of

industries to be misallocated. We can also use a variant of that instrumental variable where we lag the industry composition by one period.

The results are reported in table 19. As can be seen from this table, these instruments are often weak but yield estimates for the effect of the misallocation of output on the output per worker that are consistent with our OLS estimates above.

6.3 Simulations

The general idea of the simulations performed here is the following.¹⁶ From the data, we know the misallocation of all factors of production and the distribution of total factor productivity across establishments. We also know how factors covary across establishments. Finally, we also know the factor shares that were estimated empirically together with total factor productivity. We can then simulate hypothetical economies with a given amount of factor misallocation to match the data. We can also simulate alternative hypothetical economies with a marginally different amount of misallocation for one particular factor. We can then compute the change of output associated with the change in misallocation for one factor. The hypothetical effects of marginal changes in factor misallocation can then be compared with the effects we estimate with regression (7).

This exercise, which can also be conducted to assess the effect of factor misallocation on output misallocation, allows us to assess whether our empirical results are in line with the predictions of a model for which the production function is as we estimate it and factors are distributed as in the data at hand. To implement this approach, the main problem is that there is no unique mapping from our empirical measures of misallocation and covariances between factors and productivity across establishments to hypothetical distributions of factors across establishments. We must thus make distributional assumptions. For the problem to remain easily computable, we need to impose log normal distributions.¹⁷

¹⁶We are very grateful to Yu Wang for her help with the modelling.

¹⁷Even when imposing such assumptions, there is no guarantee of uniqueness as made clear below.

Our problem can be stated more precisely as follows. There are 5 variables, output Y , productivity φ , land and buildings T , other fixed assets K , and employment L which are linked by the production function described by equation (1), which we repeat here: $Y_i = e^{\varphi_i} T_i^\alpha K_i^\beta L_i^\gamma$. The marginal distributions of φ , T , K , and L and the correlations between any pair of these variables can be observed in the data.

The objective of the algorithm is to recover the joint-distribution of (φ, T, K, L) from the marginal distributions (which we observe) and their correlations (which we also observe). To keep the problem tractable, we assume that (φ, T, K, L) follows a multivariate lognormal distribution.

To understand the essence of our approach, suppose a multivariate distribution $X_i \sim \mathcal{N}(\mu_i, \sigma_{ii})$ with covariances σ_{ij} . Then, the following joint distribution can satisfy the constraint:

$$f_X = \frac{1}{\sqrt{(2\pi)^4 |\Sigma|}} \exp(-0.5(X - \mu)' \Sigma^{-1} (X - \mu)), \quad (15)$$

where X is a vector of multivariate lognormally distributed variables, μ the vector of their means and $\Sigma_{ij} = \sigma_{ij}$.

To illustrate the working of our approach, consider a pair (X_1, X_2) of bivariate lognormal random variables with correlation coefficient ρ derived from the bivariate normal with marginal means μ_1 and μ_2 and standard deviations σ_1 and σ_2 and correlation coefficient ρ_N . Then, it is well known that:

$$\rho = \frac{\exp(\rho_N \sigma_1 \sigma_2) - 1}{\sqrt{[\exp(\sigma_1^2) - 1] [\exp(\sigma_2^2) - 1]}}. \quad (16)$$

This means that given ρ , μ_1 , μ_2 , σ_1 , and σ_2 , we can recover at least one joint-distribution function for the underlying normal random variables, and therefore, the joint-distribution function of lognormally distributed variables. This approach can be easily extended to four variables.

The steps of the algorithm are the following:

1. Take one year of data for both the organised and the unorganised sectors.

2. Calibrate the production function (1) using parameters estimated in Duranton *et al.* (2015).
3. Calibrate the distributions of φ , L , K , and T . This can be done in four different ways:
 - (a) Full-sample-correlation calculated from data (correlation 1).
 - (b) Average-within-district-correlation calculated from data (correlation 2).
 - (c) Full-sample-correlation between φ and (L,K,T) and zero between L , K , and T (correlation 3).
 - (d) Average-within-district-correlation between φ and (L,K,T) and zero between L , K , and T (correlation 4).
4. For each of the four cases, simulate random numbers for these four variables.
5. Calculate the following quantities $\Sigma Y / \Sigma L$, M^Y , M^L , M^T , and M^K associated to this baseline
6. Slightly change the correlations of (φ,L) , (φ,K) , (φ,T) , respectively.
7. Simulate random numbers for these four variables again.
8. Calculate the same five indices
9. Calculate $\Delta(\Sigma Y / \Sigma L) / \Delta M^X$ and $\Delta M^Y / \Delta M^X$ for $X = L,K,T$.
10. The number of simulation is 800

In the interest of space, the full results (4 correlations and 5 years of data with different sampling options) are not reported here. Table 20 reports only results for 2010. Recall that we can consider four different correlations among factors and productivity: (1) those that we observe in the data in the aggregate, (2) those than we observe on average within district, (3) the aggregate misallocation measures that we observe in the data but setting the covariances across factors to zero, and (4) the average misallocation measures that we observe within districts but setting covariances across factors to zero.

The first important result from table 20 is a large negative effect of the misallocation land and buildings. Across all simulations, the coefficient on the misallocation of land buildings on the log of output per worker is equal to -0.54 . In the simulations that correspond most closely to our data, which are in panel C (where sample size is most restricted and where we consider only the within district correlations), the coefficient coming out of the simulations is -0.44 . In the estimations of Duranton *et al.* (2015), the baseline coefficient on the misallocation of land and buildings estimated across all years is equal to -0.64 and to -0.49 when imposing district fixed effects. When note that the match is less good when we use simulations for other years of data.

For the misallocation of employment, the average coefficient coming from the simulations is -0.12 . In the results reported by Duranton *et al.* (2015), this estimated coefficient is -0.10 in the baseline and -0.09 with district fixed effects. It is insignificant in both cases. For the misallocation of other fixed assets, the average coefficient from the simulation is -0.32 . In the results reported by Duranton *et al.* (2015), this estimated coefficient is close to zero but negative and significant. These empirical results are mostly driven by a few districts with highly negative values of this misallocation index for a some years. When using another measure of TFP, a coefficient of -0.24 is obtained. Hence, despite some differences across years in the simulations, and less good of a match for other fixed assets, the simulations coincide reasonably well with our empirical results. Of course, the match is far from perfect but finding coefficients of similar magnitude is somewhat remarkable given how little structure we impose to the data we simulate.

We reach the following conclusion. Using instrumental variables, we show above that the estimates of Duranton *et al.* (2015) regarding the effect of misallocation on output per worker are unlikely to be driven by reverse causality. We show here that the allocation of factors across establishments, which we measure through the covariances between factors and TFP and among factors, is able to generate the same type of effect as we estimate from the data. This shows that the results we find are those that we should find in a situation where factor misallocation is a causal force behind output per worker. It seems

unlikely that a missing variable that affects output per worker and factor misallocation would affect them in just the exact way that would preserve the expected structural effect of factor misallocation on output per worker.

7. Conclusions

We can draw a number of conclusions from this wide-ranging analysis.

First, we proposed a new factor decomposition of our misallocation indices. In regressions of output misallocation on factor misallocation, the estimated coefficients are as predicted by this decomposition. This provides an important validation of the quality of our data and our methodology.

Second, we also proposed a new within/between decomposition. We applied it to a variety of dimensions. Our main results are the following. The national economy is very much like a larger version of a typical district when it comes to misallocation. There are nonetheless some interesting patterns across districts. Larger and more productive districts appear to be more misallocated. However, they also receive proportionately more factors. These two effects offset each other in determining national misallocation. We also find that within-district misallocation takes place within industries as well as across industries, to the extent that productivity differences across industries can be well measured. Interestingly, both the organised and unorganised sectors contribute about equally to misallocation. Importantly, the organised sector enjoys the use of disproportionately more factors, which is efficient given the superior productivity of this sector. Finally, we also uncovered interesting patterns regarding the way gender plays into misallocation.

Third, we also analysed data for services to mirror our previous analysis for manufacturing. Just like for manufacturing we found strong evidence that in services factor misallocation breeds output misallocation. Similarly, we also found that misallocation had a strong negative effect on output per worker. There is an important difference between manufacturing and service regarding land and buildings. The key factor behind

misallocation in manufacturing is land and buildings while labour appears to matter most for services.

We also greatly expanded our work on the effect of economic policies on misallocation. We could provide evidence that labour reforms towards greater worker protection worsened misallocation whereas land reforms improved it. We also investigated a number of changes in the regulation of industries. We found that delicensing led to a reduction in misallocation just like the liberalisation of foreign direct investment. Interestingly, these effects took a long time to materialise and we found evidence of short-term effects often going in the opposite direction. In addition, note that to explore these policies we had to consider different types of observations, industries within states as opposed to all industries aggregated in districts. This allowed us to check further that misallocation breeds misallocation and that misallocation reduces output per worker.

We also deepened our previous analysis and took some steps towards the estimation of the causal effect of misallocation on output per worker. We developed an instrumental variable approach using lags of misallocation and predictions of misallocations using the local industry composition of activity interacted with the tendency of different industries to be misallocated. This approach essentially confirmed our previous results. We also developed a new simulation approach where we replicate an economy with a similar joint distribution of factors and productivity as a typical district in our data. We then make a small change to a measure of misallocation in a counterfactual simulation to assess how much this change in misallocation affects output per worker. Again, the simulation results are broadly consistent with our empirical findings.

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