Misallocation or Mismeasurement?

Mark Bils
University of Rochester and NBER

Peter J. Klenow
Stanford University and NBER

Cian Ruane *
Stanford University

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Abstract

Revenue per unit of inputs differs greatly across plants within countries such as the U.S. and India. Such gaps may reflect misallocation, which lowers aggregate productivity. But differences in measured average products need not reflect differences in true marginal products. We propose a way to estimate the gaps in true marginal products in the presence of measurement error in revenue and inputs. Applying our correction to manufacturing plants in the U.S. eliminates an otherwise mysterious sharp downward trend in allocative efficiency from 1978–2007. For Indian manufacturing plants from 1985–2011, meanwhile, we estimate that true marginal products were only one-half as dispersed as measured average products.

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1. Introduction

Revenue per unit of inputs differs substantially across establishments within narrow industries in the U.S. and other countries. See the survey by Syverson (2011). One interpretation of such gaps is that they reflect differences in the value of marginal products for capital, labor, and intermediate inputs. Such differences may imply misallocation, with negative consequences for aggregate productivity. This point has been driven home by Restuccia and Rogerson (2008) and Hsieh and Klenow (2009). See Hopenhayn (2014) for a survey of the growing literature surrounding this topic.

But differences in measured average products need not imply differences in true marginal products. For one, ratios of marginal products across establishments only map to ratios of average products under Cobb-Douglas production. Second, and perhaps more important, measured differences in revenue per inputs could simply reflect poor measurement of revenue or costs. For example, the capital stock is typically a book value measure that need not closely reflect the market value of physical capital. Misstatement of inventories will contaminate and distort measures of gross output and intermediates, since these are inferred in part based on the change in finished, work in process, and materials inventories. See White et al. (2016) for how the U.S. Census Bureau tries to correct for measurement errors in its survey data on manufacturing plants.[1]

We propose and implement a method to quantify the extent to which measured average products reflect true marginal products in the presence of measurement error and overhead costs. Our method is able to detect measurement error in revenue and inputs which is additive (as with overhead costs) but whose variance can scale up with the plant's true revenue and inputs. Our method cannot identify proportional measurement error, and therefore may yield a lower bound on the magnitude of measurement error.

[1]Bartelsman et al. (2013) and Asker et al. (2014) discuss why revenue productivity need not reflect misallocation even aside from measurement error, due to overhead costs and adjustment costs, respectively.

The intuition for our method is as follows. Imagine a world with constant (proportional) differences in true marginal products and constant additive measurement error in revenue and inputs. The only shocks are to idiosyncratic plant productivity, which move true revenue and inputs around across plants in the same proportion. Now, the ratio of marginal to average products is simply the elasticity of revenue with respect to inputs. Thus if marginal products reflect average products, then the elasticity of revenue with respect to inputs should look similar for plants with high and low average products. If, in contrast, a high average product plant has no higher marginal product, then its elasticity of revenue with respect to inputs should be lower. When a plant's revenue is overstated and/or its inputs are understated, measured revenue will be less responsive to changes in measured inputs. Figure 1 illustrates this by plotting the ratio of marginal to average products against revenue products under the two polar cases.

Another way to see this is to note that the ratio of first differences (the change in revenue divided by the change in inputs) is an independent measure of the marginal product. Constant measurement error (or a constant overhead cost) simply drops out with first-differencing. Thus, if true marginal products are constant over time for a given plant, one could simply calculate the dispersion of true marginal products from the dispersion of first-differences. Slightly less restrictive, if true marginal products followed a random walk, one could regress first differences on levels and the coefficient would reveal the share of dispersion in levels due to true marginal product differences.

Yet another framing is to suppose that measurement error is additive but i.i.d. over time, so that levels and first differences of revenue relative to inputs provide independent signals of the true dispersion in marginal products. In this event, by taking the covariance between first differences and levels (average products), one could estimate the variance of the true marginal products. The ratio of the covariance to the variance of the levels would be an estimate of the share of true dispersion in levels.

As these examples illustrate, panel data can be used to improve estimates of true marginal product dispersion in the presence of measurement error (and overhead costs). Our method nests the stark examples given above, allowing for changes in true marginal products and for serially correlated (but possibly mean-reverting) measurement error over time for a given plant. The key restriction we do require is that the additive measurement error be orthogonal to the true marginal product. As we will show, our specification involves regressing revenue growth on input growth, average products, and their interaction. The coefficient on the interaction term will tell us how much measurement error is contributing to the dispersion in measured average products.

We apply our methodology to U.S. manufacturing plants from 1978–2007 and formal Indian manufacturing plants from 1985–2011. The U.S. data is from the Annual Survey of Manufacturers (ASM) plus ASM plants in Census years, both from the Longitudinal Research Database (LRD). The Indian data is from the Annual Survey of Industries (ASI). The LRD contains about 50,000 ASM plants per year, and the ASI about 43,000 plants per year.

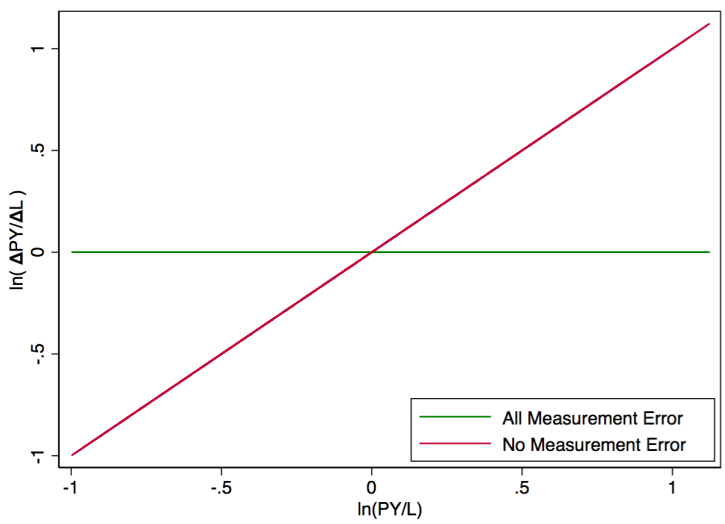
We first report estimates of allocative efficiency without correcting for measurement error. The U.S. exhibits a severe decline, by the end of the sample seemingly producing only $\frac{1}{3}$ as much as it could by equalizing marginal products across plants – down from about $\frac{2}{3}$ allocative efficiency at the beginning of the sample. If true, this plunge reduced annual TFP growth rate by 2.5 percent per year over from 1978–2007. By comparison, we estimate that Indian manufacturing operated at about $\frac{1}{2}$ efficiency, with a fair bit of volatility from year to year but no clear trend despite major policy reforms.

Once we correct for measurement error, U.S. allocative efficiency is much higher (above $\frac{4}{5}$) with no clear trend and little volatility. Thus measurement error appears to be a growing problem in Census ASM plant data. In the Indian ASI, measurement error accounts for about $\frac{1}{2}$ of the dispersion in average products across plants. Correcting for it likewise leaves Indian allocative efficiency without a clear trend or much volatility. Comparing the two countries, alloca-

tive efficiency appears to consistently lift U.S. manufacturing productivity by 30 to 40 relative to that in India.

The rest of the paper proceeds as follows. Section 2 presents a simple model and numerical example wherein both measurement error and distortions are fixed over time. Section 3 presents the full model, which allows both measurement error and distortions to change over time. Section 4 describes the U.S. and Indian datasets, and raw allocative efficiency patterns in the absence of our correction for measurement error. Section 5 lays out our method for quantifying measurement error, and applies it to the panel data on manufacturing plants in the U.S. and India. Section 6 shows how correcting for measurement error affects the picture of allocative efficiency in the U.S. and India.

Figure 1: Measured Marginal Products vs TFPR



2. A Numerical Example from an Illustrative Model

In order to convey intuition for our methodology, we first present a simple model and numerical example. We assume the economy has a fixed number of workers L and a single, competitive final goods sector producing aggregate output Y. Aggregate output is, in turn, produced by CES aggregation of the output Y_i of

N intermediate goods producers with elasticity of substitution ϵ:

$$Y = \left(\sum_{i=1}^{N} Y_i^{1-\frac{1}{\epsilon}} \right)^{\frac{1}{1-\frac{1}{\epsilon}}}$$

The price index of the final good is given by $P = \left(\sum_i P_i^{1-\epsilon} \right)^{\frac{1}{1-\epsilon}}$ and is normalized to 1. Intermediate firms produce output using a linear production technology in labor under heterogeneous productivities: $Y_i = A_i L_i$. These firms are monopolistically competitive and face a downward sloping demand curve: $Y_i \propto P_i^{-\epsilon}$. They maximize profits taking as given Y, P, the wage w, and an idiosyncratic revenue distortion τ_i:

$$\Pi_i = \frac{1}{\tau_i} P_i Y_i - w L_i$$

The researcher observes only *measured* revenue $\widehat{P_i Y_i} \equiv P_i Y_i + g_i$ and *measured* labor $\widehat{L}_i \equiv L_i + f_i$. Given the assumed CES demand structure, firms charge a common markup over their marginal cost (gross of the distortion):

$$P_i = \left(\frac{\epsilon}{\epsilon - 1} \right) \times \left(\tau_i \cdot \frac{w}{A_i} \right)$$

True revenue is therefore proportional to the product of true labor times and the idiosyncratic distortion:

$$P_i Y_i \propto \tau_i \cdot L_i \tag{1}$$

Thus variation across firms in true average revenue products $\left(\frac{P_i Y_i}{L_i} \right)$ is solely due to the distortion. Variation in *measured* average revenue products (TFPR), however, reflects both the distortion and measurement errors:

$$TFPR_i \equiv \frac{\widehat{P_i Y_i}}{\widehat{L}_i} \propto \left[\tau_i \times \frac{1 + g_i/(P_i Y_i)}{1 + f_i/L_i} \right].$$

While our methodology will allow both the true distortions and measurement errors to vary over time, to convey intuition we make the a number of simplifying assumptions in this section:

1. The true distortions τ_i are fixed over time
2. The additive measurement error terms g_i and f_i are fixed over time
3. The idiosyncratic productivities A_{it} are time-varying

The assumption that additive measurement error is fixed over time means that first differences of measured revenue and labor are exactly equal to first differences in true revenue and labor: $\blacktriangle\widehat{P_iY_i} = \blacktriangle P_iY_i$ and $\blacktriangle\widehat{L}_i = \blacktriangle L_i$.[2] The assumption that distortions are fixed over time then implies that the ratio of first differences of revenue and labor reflects only the distortion and not the measurement errors:[3]

$$\frac{\blacktriangle\widehat{P_iY_i}}{\blacktriangle\widehat{L}_i} \propto \tau_i$$

With this background, consider the numerical example of two firms in Table 1. As shown, the ratio of their measured average revenue products $\left(\frac{2.4}{0.8}\right)$ overstates the ratio of their true marginal revenue products $\left(\frac{2}{1}\right)$. Regressing the natural log of the ratio of first differences on ln(TFPR) reveals how much of the measured TFPR dispersion reflects true dispersion in marginal revenue products (distortions). The regression yields a coefficient of 1 if there is no measurement error in TFPR and a coefficient of 0 if all TFPR dispersion is due to measurement error. We illustrate this in Figure 1. For the numerical example in Table 1, we obtain a coefficient of $\left(\frac{\ln(2)-\ln(1)}{\ln(2.4)-\ln(0.8)}\right) \approx \frac{2}{3}$. This implies that roughly $\frac{2}{3}$ of the dispersion in measured average products reflects dispersion in true marginal products.

In Section 5 below we will generalize to allow for shocks to both measurement error and distortions. The intuition of the simple example will remain,

[2]We use ▲ to denote first differences *in levels* and Δ first differences in *natural logs*.
[3]This follows naturally from equation 1.

Table 1: Illustrative Numerical Example

	PY	L	$\frac{PY}{L}$	$\widehat{PY}$	$\widehat{L}$	$\frac{\widehat{PY}}{\widehat{L}}$	$\blacktriangle PY$	$\blacktriangle L$	$\frac{\blacktriangle PY}{\blacktriangle L}$
Firm 1	100	50	2	120	50	2.4	50	25	2
Firm 2	50	50	1	40	50	0.8	25	25	1

however; the covariance of two noisy measures of the distortion (ratios of levels of revenues and inputs and ratios of first differences of revenues and inputs) will provide us with an estimate of the variance of the distortion.

In the next section we present the full model and a decomposition of aggregate and sectoral TFP into allocative efficiency vs. other terms.

3. Model

3.1. Economic Environment

We consider an economy with S sectors, L workers and an exogenous capital stock K. There are an exogenous number of firms N_s operating in each sector. A representative firm produces a single final good Q in a perfectly competitive final output market. This final good is produced using gross output Q_{st} from each sector s with a Cobb-Douglas production technology:

$$Q = \prod_{s=1}^{S} Q_s^{\theta_s} \quad \text{where} \quad \sum_{s=1}^{S} \theta_s = 1$$

We normalize P, the price of the final good, to 1. The final good can either be consumed or used as an intermediate input:

$$Q = C + X.$$

All firms use the same intermediate input, with the amounts denoted X_{si} so that $X \equiv \sum_{s=1}^{S} X_s = \sum_{s=1}^{S}\sum_{i=1}^{N_s} X_{si}$. Sectoral output Q_s is a CES aggregate of the output produced by the N_s firms in sector s:

$$Q_s = \left(\sum_{i=1}^{N_s} Q_{si}^{1-\frac{1}{\epsilon}}\right)^{\frac{1}{1-\frac{1}{\epsilon}}}.$$

We denote P_s the price index of output from sector s. Firms have idiosyncratic productivity draws A_{si}, and produce output Q_{si} using a Cobb-Douglas technology in capital, labor and intermediate inputs:

$$Q_{si} = A_{si}(K_{si}^{\alpha_s} L_{si}^{1-\alpha_s})^{\gamma_s} X_{si}^{1-\gamma_s} \quad \text{where} \quad 0 < \alpha_s, \gamma_s < 1.$$

The output elasticities α_s and γ_s are sector-specific, but time-invariant and common across firms within a sector. Firms are monopolistically competitive and face a downward sloping demand curve given by $Q_{si} = Q_s \left(\frac{P_{si}}{P_s}\right)^{-\epsilon}$.[4] Firms also face idiosyncratic labor distortions τ_{si}^L, capital distortions τ_{si}^K and intermediate input distortions τ_{si}^X. They maximize profits Π_{si} taking input prices as given.

$$\Pi_{si} = R_{si} - (1+\tau_{si}^L) w L_{si} - (1+\tau_{si}^K) r K_{si} - (1+\tau_{si}^X) P X_{si}$$

where $R_{si} \equiv P_{si} Q_{si}$ is firm revenue.

3.2. Aggregate TFP

We define aggregate TFP as aggregate real consumption (or equivalently value-added) divided by an appropriately weighted Cobb-Douglas bundle of aggregate capital and labor:

$$TFP \equiv \frac{C}{L^{1-\tilde{\alpha}} K^{\tilde{\alpha}}} \quad \text{where} \quad \tilde{\alpha} \equiv \frac{\sum_{s=1}^{S} \alpha_s \gamma_s \theta_s}{\sum_{s=1}^{S} \gamma_s \theta_s}$$

[4] We assume that the firms treat P_s and Q_s as exogenous.

We show in the Model Appendix that

$$TFP = \overline{T} \times \prod_{s=1}^{S} TFP_s^{\frac{\theta_s}{\sum_{s=1}^{S} \gamma_s \theta_s}}.$$

$\overline{T}$ captures the effect of the *sectoral* distortions τ_s^L, τ_s^K and τ_s^X, which are the revenue-weighted harmonic means of the idiosyncratic firm-level distortions.[5] Sectoral TFP is then:

$$TFP_s \equiv \frac{Q_s}{(K_s^{\alpha_s} L_s^{1-\alpha_s})^{\gamma_s} X_s^{1-\gamma_s}}$$

Within-sector misallocation lowers TFP_s. The sectoral distortions will induce a *cross-sector* misallocation of resources, which will show up in $\overline{T}$. While cross-sector misallocation is of interest, it is not the focus of this paper. We therefore leave it to future research to determine how important this could be in determining cross-country aggregate TFP gaps.

3.3. Sectoral TFP Decomposition

Sector-level TFP is a function of firm-level productivities and distortions:

$$\begin{aligned} TFP_s &= \left[\sum_{i=1}^{N_s} A_{si}^{\epsilon-1} \left(\frac{\tau_{si}}{\tau_s} \right)^{1-\epsilon} \right]^{\frac{1}{\epsilon-1}} \\ \text{where} \quad \tau_{si} &\equiv \left[\left(1+\tau_{si}^L\right)^{1-\alpha_s} \left(1+\tau_{si}^K\right)^{\alpha_s} \right]^{\gamma_s} \left(1+\tau_{si}^X\right)^{1-\gamma_s} \\ \text{and} \quad \tau_s &\equiv \left[\left(1+\tau_s^L\right)^{1-\alpha_s} \left(1+\tau_s^K\right)^{\alpha_s} \right]^{\gamma_s} \left(1+\tau_s^X\right)^{1-\gamma_s} \end{aligned}$$

We can go one step further, and decompose sectoral TFP into the product of four terms: allocative efficiency (AE_s), a productivity dispersion term (PD_s), average productivity ($\bar{A}_s$) and a variety term ($N_s^{\frac{1}{\epsilon-1}}$).

[5] $(1+\tau_s^L) \equiv \left[\sum_{i=1}^{N_s} \frac{R_{si}}{R_s} \frac{1}{1+\tau_{si}^L} \right]^{-1}$ and similarly for $(1+\tau_s^K)$ and $(1+\tau_s^X)$. The Model Appendix expresses sectoral distortions as a function only of firm distortions and productivities.

$$TFP_s = \underbrace{\left[\frac{1}{N_s}\sum_{i}^{N_s}\left(\frac{A_{si}}{\tilde{A}_s}\right)^{\epsilon-1}\left(\frac{\tau_{si}}{\tau_s}\right)^{1-\epsilon}\right]^{\frac{1}{\epsilon-1}}}_{AE_s=\text{Allocative Efficiency}} \times \underbrace{\left[\frac{1}{N_s}\sum_{i}^{N_s}\left(\frac{A_{si}}{\bar{A}_s}\right)^{\epsilon-1}\right]^{\frac{1}{\epsilon-1}}}_{PD_s=\text{Productivity Dispersion}} \times \underbrace{N_s^{\frac{1}{\epsilon-1}}}_{\text{Variety}} \times \underbrace{\bar{A}_s}_{\text{Average Productivity}}$$

$\tilde{A}$ is the power mean of idiosyncratic productivities, $\left[\frac{1}{N_s}\sum_{i=1}^{N_s}(A_{si})^{\epsilon-1}\right]^{\frac{1}{\epsilon-1}}$, and $\bar{A}$ is the geometric mean of idiosyncratic productivities $\prod_{i=1}^{N_s} A_{si}^{\frac{1}{N_s}}$. AE_s is maximized and equal to 1 when there is no variation in the distortions across firms ($\tau_{si} = \tau_s$ $\forall i$). The productivity dispersion term (PD_s) is the ratio of the power mean to the geometric mean. Because $\epsilon > 1$, greater dispersion in firm-level productivities induces a reallocation of labor towards the most productive firms, thereby increasing sectoral TFP. $N_s^{\frac{1}{\epsilon-1}}$ captures the productivity gains from expanding the set of varieties available to sectoral goods producers. Finally, it is clear why increases in average productivity ($\bar{A}_s$) should increase sectoral TFP.

The goal of this paper is to present a methodology for inferring allocative efficiency (AE_s) from plant-level data while allowing for measurement error. In the next section we briefly describe the U.S. and Indian datasets we use, present the model-based approach to inferring allocative efficiency in the *absence* of measurement error, and show raw allocative efficiency patterns in the data.

4. Inferring Allocative Efficiency

4.1. The Datasets

Our sample from the Indian Annual Survey of Industries (ASI) runs from 1985 to 2011.[6] The ASI is a nationally representative survey of the formal manufacturing sector in India. The coverage is all plants with more than 10 workers using

[6]The surveys cover accounting years (e.g. 1985-1986), but we will refer to each survey by the earlier of the two years covered.

power, and all plants with more than 20 workers not using power. Plants fall into two categories: *Census* and *Sample*. *Census* plants are surveyed every year, and consist of plants with workers above a given threshold as well as all plants in 12 of the industrially 'backwards' states.[7] *Sample* plants are sampled at random every year within each state $\times$ 3-digit industry group, and sampling weights are provided. We construct a set of 50 manufacturing sectors that are consistently defined throughout our time period.[8] We also construct an aggregate capital deflator using data on gross capital formation from the Reserve Bank of India, and we construct sectoral gross output deflators using wholesale price indices from the Indian Office of the Economic Advisor. Further details on the construction of sectors and deflators are provided in the Data Appendix.

The datasets we use for the U.S. are the Annual Survey of Manufactures (ASM) and the Census of Manufactures (CMF), which are surveys carried out by the U.S. Census Bureau. We put together a long panel from 1978 to 2007. The ASM is conducted annually except for years ending in 2 or 7. In years ending in 2 or 7 the CMF is conducted. The coverage of both the CMF and ASM are all plants with at least one paid employee. The difference between the surveys is that the CMF is a census which covers all establishments with certainty while the ASM is a survey which covers large establishments with certainty but includes only a sample of smaller plants.[9] The ASM sample of plants is redrawn in years beginning with 3 or 8. In order to avoid any large changes in sample size over time, we use only the 'ASM' sample plants in CMF years.[10] We use the harmonized sectoral classification from Fort and Klimek (2016) at the NAICS 3-digit level; we thereby have balanced sectoral panel of 86 sectors.[11]. We construct sectoral

[7]The threshold number of workers to be a *Census* plant varies across years. See the Data Appendix for more details regarding sampling changes in the ASI over time.

[8]The official sectoral classification (NIC) changed in 1987, 1998, 2004 and 2008. We use official NIC concordances to construct our harmonized classification.

[9]As with the Indian ASI, sampling weights are provided in the ASM in order to produce moments representative of the entire population of establishments with at least one employee.

[10]For convenience we will therefore refer to our U.S. dataset as the ASM.

[11]The Fort-Klimek (FK) sectors deal with the large reclassification of manufacturing plants into the service sector during the SIC to NAICS transition. It is available at the 6-digit NACIS level, but we use the 3-digit level to have a similar number of sectors in the U.S. and India.

output and material deflators from the NBER-CES database and sectoral capital stock deflators from the BEA. Further details on the sectoral classification and deflators are in the Data Appendix.

Our main variables of interest are plant sales, employment, labor costs, the capital stock, stocks of inventories, and intermediate input expenditures. Revenue is constructed to include the value of product sales and changes in finished and semi-finished good inventories. Employment includes both paid and unpaid labor. Labor costs include wages, salaries, bonuses and any supplemental labor costs. The capital stock includes inventories, and is constructed as the average of the beginning and end of year stocks. In India, the book value of the capital stock is reported directly so we use this. In the U.S. our capital stock is measured as the market value in 1997 dollars. Intermediate inputs include materials, fuels, and other expenditures.[12]

In addition to dropping plants that have missing values for key variables, we trim the 1% tails of the average revenue products of capital, labor, and intermediates as well as productivity (TFPQ, to be defined shortly). Our final sample sizes are 1,428,000 plant-year observations for the U.S. and 844,875 plant-year observations for India. The data cleaning steps are summarized in more detail in Table 11 of the Data Appendix.

4.2. Evidence of Measurement Error in the Indian ASI

Table 2 provides evidence of the frequency of some observable forms of measurement error in the Indian ASI. First, for 12% of observations the reported plant age is not consistent with what was reported in the previous year. Next, we compare the reported values of the beginning-of-year (BOY) stocks and end-of-year (EOY) stocks of capital, goods inventories and materials inventories from the previous year.[13] Differences between the BOY value in the current year and EOY value in the previous year are likely to reflect errors in reporting. We

[12] See the Data Appendix for details on what is included in each variable for the U.S. and India.
[13] Beginning-of-year stocks are the values on April 1st, and end-of-year stocks on March 31st.

Table 2: Measurement error in the ASI

	Frequency	Magnitude
Age	12.4%	4 years
EOY & BOY capital stocks	25.7%	15.4%
EOY & BOY goods inventories	22.0%	24.8%
EOY & BOY materials inventories	22.3%	20.2%

Note: There is measurement error in age if age in year t is not equal to 1 + age in year $t-1$. The magnitude of this measurement error is the median absolute deviation. There is measurement error in stocks and inventories if the deviation of the BOY (beginning-of-year) value in year t from the EOY (end-of-year) value in year $t-1$ is greater than 1%. The magnitude of this measurement error is the standard deviation of the absolute value of the percentage measurement error.

find that these reporting errors are both frequent and large in magnitude. For example, for 25.7% of observations the reported BOY value of the capital stock is not within 1% of the previous year's EOY value. The standard deviation of the absolute value of the percentage measurement error is 15.4%. Mismeasurement of capital and inventories is highly relevant for allocative efficiency calculations. Capital is itself a measured input, while changes in the stocks of inventories affect measures of output produced and intermediate inputs used.

4.3. Inferring Allocative Efficiency

Continuing to use $\widehat{\ }$'s to differentiate *measured* values from true values, we define TFPR and TFPQ as:

$$TFPR_{si} \equiv \frac{\widehat{R}_{sit}}{(\widehat{K}_{sit}^{\alpha_s}\widehat{L}_{sit}^{1-\alpha_s})^{\gamma_s}\widehat{X}_{si}^{1-\gamma_s}}$$

$$TFPQ_{sit} \equiv \frac{\left(\widehat{R}_{sit}\right)^{\frac{\epsilon}{\epsilon-1}}}{(\widehat{K}_{sit}^{\alpha_s}\widehat{L}_{sit}^{1-\alpha_s})^{\gamma_s}\widehat{X}_{sit}^{1-\gamma_s}}$$

In the absence of measurement error TFPR would be proportional to the distortions and TFPQ would be proportional to productivity:

$$\frac{R_{sit}}{(K_{sit}^{\alpha_s} L_{sit}^{1-\alpha_s})^{\gamma_s} X_{sit}^{1-\gamma_s}} \propto \tau_{sit}$$

$$\frac{(R_{sit})^{\frac{\epsilon}{\epsilon-1}}}{(K_{sit}^{\alpha_s} L_{sit}^{1-\alpha_s})^{\gamma_s} X_{sit}^{1-\gamma_s}} \propto A_{sit}$$

Inferred sectoral allocative efficiency is given by:

$$\widehat{AE}_{st} = \left[\sum_{i=1}^{N_{st}} \left(\frac{TFPQ_{sit}}{TFPQ_{st}} \right)^{\epsilon-1} \left(\frac{TFPR_{sit}}{TFPR_{st}} \right)^{1-\epsilon} \right]^{\frac{1}{\epsilon-1}}$$

where $\quad TFPQ_{st} = \left[\sum_{i=1}^{N_{st}} TFPQ_{sit}^{\epsilon-1} \right]^{\frac{1}{\epsilon-1}}$

and $\quad TFPR_{st} = \left(\frac{\epsilon}{\epsilon-1} \right) \left[\frac{MRPL_{st}}{(1-\alpha_s)\gamma_s} \right]^{(1-\alpha_s)\gamma_s} \left[\frac{MRPK_{st}}{\alpha_s \gamma_s} \right]^{\alpha_s \gamma_s} \left[\frac{MRPX_{st}}{1-\gamma_s} \right]^{1-\gamma_s}$

$MRPL_{st}$, $MRPK_{st}$ and $MRPX_{st}$ are the revenue-weighted harmonic mean values of the marginal products of labor, capital and intermediates, respectively:

$$MRPK_{st} = \left[\sum_i \frac{\widehat{R}_{si}}{\widehat{R}_{st}} \frac{1}{MRPK_{sit}} \right]^{-1}$$

$$MRPK_{sit} = \left(\frac{\epsilon-1}{\epsilon} \right) \alpha_s \gamma_s \frac{\widehat{R}_{sit}}{\widehat{K}_{sit}}$$

Aggregating across sectors we obtain inferred aggregate allocative efficiency, which is equal to true allocative efficiency when there is no measurement error:

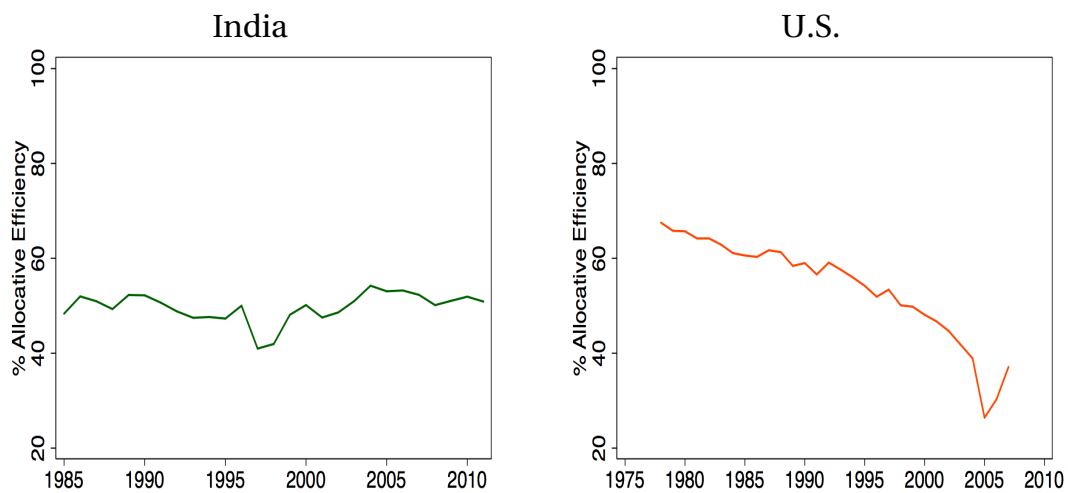
$$\widehat{AE}_t = \prod_{s=1}^{S} \widehat{AE}_{st}^{\frac{\theta_{st}}{\sum_{s=1}^{S} \gamma_s \theta_{st}}}$$

In order to obtain estimates of allocative efficiency over time for the U.S. and India we need to pin down a number of parameters in the model. Based on

evidence from Redding and Weinstein (2016), we pick a value of $\epsilon = 4$ for the elasticity of substitution across plants. Allocative *inefficiencies* are amplified under higher values of this elasticity. We infer α_s and γ_s based on country-specific average sectoral cost shares (assuming a rental rate of 20% for India and 15% for the U.S.). We allow the aggregate output shares θ_{st} to vary across years, and base them on country-specific sectoral shares of manufacturing output.

4.4. Time-Series Results

Figure 2: Allocative Efficiency in India and the U.S.

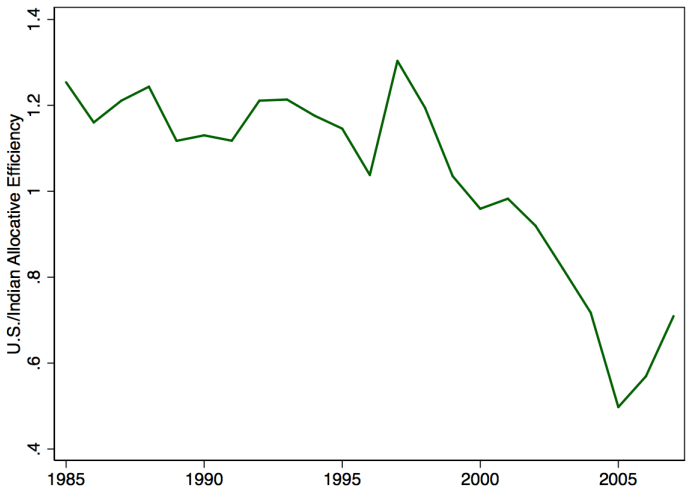


Source: The Annual Survey of Industries (ASI) for India and the Annual Survey of Manufactures (ASM) for the U.S. The figure shows the % allocative efficiency for both countries. Average allocative efficiency is 49% in India and 54% in the U.S. over the respective sample periods.

Figure 2 plots inferred allocative efficiency for the U.S. and India over their respective samples. Average allocative efficiency over the sample is 49% in India, and 54% in the U.S.[14] While allocative efficiency is not trending in India, there is a remarkable decrease in allocative efficiency in the U.S. between 1978

[14]Average gains from full reallocation are therefore 102% for India and 95.6% for the U.S. In contrast, Hsieh and Klenow (2009) found 40-60% higher potential gains from reallocation in India than the U.S. Our estimates diverge for a number of reasons: gross output (us) vs. value added (them); 1978–2007 ASM plants vs. 1987, 1992 and 1997 Census plants; and trimming of 1% tails in the U.S. vs. 2% (they inconsistently trimmed 2% for the U.S. and only 1% for India).

Figure 3: Allocative Efficiency: U.S. Relative to India



Source: Indian Annual Survey of Industries (ASI) and U.S. Annual Survey of Manufactures (ASM). The figure plots the ratio of U.S. allocative efficiency to Indian allocative efficiency for the years 1985 to 2007 (years in which the datasets overlap).

and 2007. Allocative efficiency is actually *lower* in the U.S. than in India by the mid-2000s. Figure 3 plots the ratio of U.S. to Indian allocative efficiency for the overlapping years of the samples.

In the next section we present out methodology for correcting inferred allocative efficiency for measurement error.

5. Measurement Error

Calculations of misallocation, including those just presented, interpret plant differences in measured average revenue products (TFPR) as differences in true marginal products. In many of these studies the underlying plant data are longitudinal. Given such data, it is natural to ask if plants reporting higher average revenue products actually display larger revenue responses to input changes, as expected if their inputs truly exhibit higher marginal revenue. Of course, any observed input/revenue change need not identify true marginal revenue, as this can be counfounded by the source of the changes. For instance, some input and revenue changes may be measured with error. We will show, however, that

by projecting the elasticity of revenue with respect to inputs on TFPR, we can answer the question: To what extent do plants with higher measured average products exhibit higher true marginal products? The logic is similar to using the covariance of two noisy measures of a variable, here noisy measures of a plant's marginal revenue product, to recover a truer measure of the variable.

Consider the following description of measured inputs $\widehat{I}$ and measured revenue $\widehat{R}$ for plant i (year subscripts implicit):

$$\widehat{I}_i \equiv \phi_i \cdot I_i + f_i$$
$$\widehat{R}_i \equiv \chi_i \cdot R_i + g_i$$

where I_i and R_i denote true inputs and revenues, f_i and g_i reflect additive measurement errors, while ϕ_i and χ_i are multiplicative errors.[15] We treat the impact of measurement error in inputs as common across different inputs (capital, labor, intermediates). We return to this issue at the end of this section.

For the setting from Section 2, with profit maximization a plant's $TFPR$ is

$$TFPR_i \equiv \frac{\widehat{R}_i}{\widehat{I}_i} \propto \tau_i \left(\frac{\widehat{R}_i}{R_i} \frac{I_i}{\widehat{I}_i} \right) .$$

Absent measurement error, $TFPR_i$ provides a measure of plant i's distortion, τ_i. But, to the extent revenue is overstated, or inputs understated, $TFPR_i$ will overstate τ_i. In that circumstance, the plant's marginal revenue product is *less* than implied by its $TFPR_i$.

The growth rate of $TFPR$ will reflect the growth rate of measurement error as well as the growth rate of τ_i:

$$\Delta TFPR_i \; = \; \Delta \tau_i \; + \; \Delta \left(\frac{\widehat{R}_i}{R_i} \right) \; - \; \Delta \left(\frac{\widehat{I}_i}{I_i} \right) .$$

Δ denotes the growth rate of a plant variable relative to the mean in its sector.

[15]Note that the additive terms f_i and g_i could alternatively reflect deviations from Cobb-Douglas production. For instance, positive values for f_i, or negative for g_i, would imply marginal revenue exceeds average revenue per input.

If there are only *additive* measurement errors, then $TFPR$ growth is

$$\Delta TFPR_i = \frac{\Delta\tau_i}{\widehat{R}_i/R_i} - \left(\frac{\widehat{R}_i - R_i}{\widehat{R}_i} - \frac{\widehat{I}_i - I_i}{\widehat{I}_i}\right)\Delta I_i \; + \frac{\blacktriangle g_i}{\widehat{R}_i} \; - \; \frac{\blacktriangle f_i}{\widehat{I}_i}.$$

As above, ▲ denotes absolute change. We see that the response of $TFPR_i$ to inputs speaks to the relative size of additive measurement error in revenue versus that in inputs. $TFPR_i$ decreases with inputs if revenue is overmeasured relative to inputs ($\frac{\widehat{R}_i - R_i}{\widehat{R}_i} > \frac{\widehat{I}_i - I_i}{\widehat{I}_i}$), and increases with inputs i the reverse is true. Because it is this relative measurement error, $\frac{\widehat{R}_i - R_i}{\widehat{R}_i}$ versus $\frac{\widehat{I}_i - I_i}{\widehat{I}_i}$, that causes $TFPR_i$ to mismeasure τ_i, the response of $TFPR_i$ to inputs can identify the role of such errors in observed $TFPR_i$.

By contrast, if there are only *multiplicative* measurement errors, then the percentage change in $TFPR$ equals:

$$\Delta TFPR_i \; = \; \Delta\tau_i \; + \; \Delta\chi_i \; - \; \Delta\phi_i.$$

Here $TFPR_i$ growth provides no information on measurement error in the level of $TFPR_i$, except to the extent $\Delta\tau_i$, $\Delta\chi_i$, and $\Delta\phi_i$ project onto those errors. With proportional measurement errors, any increase in true inputs or revenue at plant i will scale up the measurement errors. Here errors that plague $TFPR_i$ as a measure of plant i's marginal revenue are perfectly related to those that contaminate the ratio of its change in revenue to change in inputs.

Going forward, we focus on purely additive measurement error. For this reason, our estimates should be viewed as a conservative assessment of the role of measurement error in generating differences in $TFPR_i$. However, we find that even this conservative assessment dramatically reduces the size and (especially) volatility of inferred misallocation. We assume that measurement errors are mean zero.[16] We further assume that measurement errors are uncor-

[16]Otherwise, changes in τ_i and A_i, by affecting the size of inputs and revenue, would affect the expected measurement error. We allow the variance of innovations to measurement error to scale with A_i and τ_i. For this reason, we do not predict that measurement errors become less important with trend growth or systematically differ between firms that differ in long-run size.

related with τ_i and A_i, though τ_i and A_i may be correlated with each other.

We next show how relating a plant's $TFPR$ to its elasticity of measured revenue with respect to inputs can address the role of measurement error in $TFPR$. We present results for both U.S. and Indian manufacturing. We then extend the methodology to consider mismeasurement in *relative* inputs across plants.

5.1. Identifying Measurement Error in $TFPR$

For exposition we first assume measurement error only in revenue, not in inputs. We bring back input errors shortly, as these are readily accommodated. Changes in plant i's measured and true inputs reflect changes: in A_i and τ_i

$$\Delta\widehat{I}_i \;=\; \Delta I_i \;=\; (\epsilon - 1)\,\Delta A_i \;-\; \epsilon\,\Delta\tau_i.$$

Meanwhile, measured revenue growth is

$$\Delta\widehat{R}_i = \Delta\widehat{I}_i + \Delta TFPR_i = \frac{R_i}{\widehat{R}_i}(\epsilon - 1)(\Delta A_i - \Delta\tau_i) + \frac{\blacktriangle g_i}{\widehat{R}_i}.$$

Our focal point is the elasticity of measured revenue with respect to measured inputs. We denote this statistic by $\widehat{\beta}$:

$$\widehat{\beta} \equiv \frac{s_{\Delta\widehat{R},\Delta\widehat{I}}}{s^2_{\Delta\widehat{I}}}$$

$\widehat{\beta}$ equals one plus the elasticity of $TFPR$ with respect to measured inputs. If revenue is overstated, then an increase in inputs will tend to decrease $TFPR$, thus reducing $\widehat{\beta}$. For instance, suppose $\Delta\tau_i = 0$, with input changes driven only by ΔA_i. This yields $\beta \equiv E[\widehat{\beta}] \equiv E[(R/\widehat{R})(1 + \frac{s_{\blacktriangle g/R,\Delta I}}{s^2_{\Delta I}})]$. This simplifies to $E[R/\widehat{R}]$, given growth in inputs and growth in measurement error are orthogonal.[17] Thus $\widehat{\beta}$ directly reveals the extent to which revenue is overmea-

[17]Going forward, we suppress the term $\frac{s_{\blacktriangle g/R,\Delta I}}{s^2_{\Delta I}}$ inside the brackets of $E[\widehat{\beta}]$, because its presence in $\widehat{\beta}$ does not affect $E[\widehat{\beta}]$. When we bring back measurement error in inputs, we similarly suppress its contributions to $\widehat{\beta}$ that do not affect $E[\widehat{\beta}]$.

sured or undermeasured. Next we relate $\widehat{\beta}$ to the plant's $TFPR$ by constructing $E\left\{\widehat{\beta} \mid \ln(TFPR)\right\} = E\left\{R/\widehat{R} \mid \ln(TFPR)\right\}$. Keep in mind that $R/\widehat{R}$ is one component in $TFPR$, as $\ln(TFPR) = \ln(\tau) - \ln(R/\widehat{R})$. Thus this addresses the question: How important is measurement error in $TFPR$?

This logic can be extended to allow for $\Delta\tau_i \neq 0$. We then have

$$E\left\{\widehat{\beta} \mid \ln(TFPR)\right\} = E\left\{\left(1+\widehat{\Omega}_\tau\right)\frac{R}{\widehat{R}} \mid \ln(TFPR)\right\},$$

where $\widehat{\Omega}_\tau \equiv (s_{\Delta\tau,\Delta I} + s_{\blacktriangle g/R,\Delta I})/s^2_{\Delta I}$. Now two factors dictate the elasticity of $\widehat{R}_i$ with respect to $\widehat{I}_i$. As before, the elasticity is decreased to the extent revenue is overmeasured. The other factor, $\widehat{\Omega}_\tau$, reflects the importance of $\Delta\tau_i$ to changes in inputs. This factor is needed because the elasticity of revenue with respect to input changes equals one if driven by ΔA_i, but only $\frac{\epsilon-1}{\epsilon}$ if caused by $\Delta\tau_i$.

The relation above can be examined non-parametrically to isolate how the term $(1+\widehat{\Omega}_\tau)R/\widehat{R}$ projects on $TFPR$. We pursue this below. But we proceed further parametrically to isolate separately how factors $R/\widehat{R}$ and $(1+\widehat{\Omega}_\tau)$ relate to plant $TFPR$. To do so, we make the further assumption that $\ln(TFPR)$'s two components, $\ln(\tau)$ and $\ln(\widehat{R}/R)$, are normally distributed.

Substituting $\left(1-\frac{\widehat{R}-R}{\widehat{R}}\right)$ for $\frac{R}{\widehat{R}}$, then approximating $\frac{\widehat{R}-R}{\widehat{R}}$ by $\ln\left(\frac{\widehat{R}}{R}\right)$, we get[18]

$$E\left\{\widehat{\beta} \mid \ln(TFPR)\right\} = E\left\{\left(1+\widehat{\Omega}_\tau\right) \mid \ln(TFPR)\right\} \cdot E\left\{\left(1-\ln\left(\frac{\widehat{R}}{R}\right)\right) \mid \ln(TFPR)\right\}$$
$$+Cov\left\{\widehat{\Omega}_\tau,\ \ln\left(\frac{\widehat{R}}{R}\right) \mid \ln(TFPR)\right\}$$

where the Cov term refers to the variables' conditional covariance.

Given $\ln(\tau)$ and $\ln(\widehat{R}/R)$ are normally distributed, the conditional expecta-

[18]This is a first-order approximation. The second-order discrepancy between $\ln\left(\frac{\widehat{R}}{R}\right)$ and $\frac{\widehat{R}-R}{\widehat{R}}$ is positive, equaling $\frac{1}{2}\left(\frac{\widehat{R}-R}{\widehat{R}}\right)^2$. The question is how this approximation error projects on $\ln(TFPR)$. Since we assume no skewness in the distribution of $\ln\left(\frac{\widehat{R}}{R}\right)$, the second-order approximation error is orthogonal to the measurement-error component in $\ln(TFPR)$.

tion of $\ln(\widehat{R}/R)$ is linear in $\ln(TFPR)$ and the conditional covariance is zero:

$$E\left\{\widehat{\beta} \mid \ln(TFPR)\right\} = E\left\{\left(1+\widehat{\Omega}_\tau\right) \mid \ln(TFPR)\right\} \cdot \left[1 - \frac{\sigma^2_{\ln \frac{\widehat{R}}{R}}}{\sigma^2_{\ln TFPR}} \ln(TFPR)\right].$$
$$\equiv E\left\{\left(1+\widehat{\Omega}_\tau\right) \mid \ln(TFPR)\right\} \cdot \left[1-(1-\lambda)\ln(TFPR)\right],$$

where

$$\lambda = \frac{\sigma^2_{\ln \tau}}{\sigma^2_{\ln TFPR}}.$$

Identifying λ answers the question: If two plants differ in $TFPR$, what fraction of that difference reflects a true difference in τ?

We first take $\ln(A_i)$ and $\ln(\tau_i)$ to be random walks, with $\Delta\tau_i$ and ΔA_i each $i.i.d.$ random variables (we generalize this shortly). In this case

$$E\left\{\widehat{\beta} \mid \ln(TFPR)\right\} = (1+\Omega_\tau)\left[1-(1-\lambda)\ln(TFPR)\right].$$

The term $(1+\Omega_\tau)$ affects the elasticity, but does not depend on $\ln(TFPR)$. So, to the extent β_i projects on $\ln(TFPR)$, we can interpret this as yielding how measurement error relates to $\ln(TFPR)$. This equation, which we call our baseline specification, shows that λ can be identified by regressing measured plant revenue growth on its input growth, but also interacting that input growth with the plant's $TFPR$. Rearranging, $\sigma^2_{\ln \tau} = \lambda \cdot \sigma^2_{\ln TFPR}$. So, conditional on observed dispersion in $TFPR$, we obtain an estimate of $\sigma^2_{\ln \tau}$ from λ.

While our baseline treats $\ln(A_i)$ and $\ln(\tau_i)$ as random walks, we want to allow that these might be stationary. It is then necessary to condition $(1+\widehat{\Omega}_\tau)$ on $\ln(TFPR)$. To illustrate why, suppose $\ln \tau_i$ takes either an extremely positive or extremely negative value. Then the expected magnitude of $\Delta\tau_i$ will be larger, as there is a tendency for $\ln \tau_i$ to regress back to its mean. Anticipated $\Delta\tau_i$ is large and negative if $\ln \tau_i$ is extremely high, and large and positive if $\ln \tau_i$ is extremely low. For this reason, $\widehat{\Omega}_\tau$ is greater at extreme values for $\ln \tau_i$. Because $\ln(TFPR_i)$ includes $\ln \tau_i$, $\widehat{\Omega}_\tau$ is also greater for extreme values of $\ln(TFPR_i)$. As an example,

suppose that $\ln(\tau_i)$ follows an AR(1) with parameter ρ. Then $E\{\Delta\tau_i\} = -(1-\rho)\ln(\tau_i)$, and $Var\{\Delta\tau_i\} = (1-\rho)^2(\ln(\tau_i))^2$.

With this example in mind, we generalize our baseline specification to allow that $E\left\{\left(1+\widehat{\Omega}_\tau\right) \mid \ln(TFPR)\right\}$ is captured by a projection on $(\ln(TFPR))^2$. That yields

$$E\left\{\widehat{\beta} \mid \ln(TFPR)\right\} = \left[\Psi + \Lambda(\ln(TFPR))^2\right] \cdot [1-(1-\lambda)\ln(TFPR)].$$

We anticipate $\Lambda \leq 0$. λ continues to equal $\frac{\sigma^2_{\ln\tau}}{\sigma^2_{\ln TFPR}}$.

Before turning to our empirical specifications, we first relax the assumption, made for exposition, that measurement error is only in revenue. Allowing measurement error in inputs, the general specification becomes

$$E\left\{\widehat{\beta} \mid \ln(TFPR)\right\} = E\left\{\left(1+\widehat{\Omega}_\tau - \widehat{\Omega}_f\right)\frac{R\widehat{I}}{\widehat{R}I} \mid \ln(TFPR)\right\},$$

where

$$\widehat{\Omega}_f \equiv \frac{s^2_{\blacktriangle f/I} - s_{\blacktriangle g/R, \blacktriangle f/I}}{s^2_{\Delta I + \blacktriangle f/I}}.$$

is the projection of measurement error $\blacktriangle f/I$ on $\Delta I + \blacktriangle f/I$.

Our baseline specification becomes

$$E\left\{\widehat{\beta} \mid \ln(TFPR)\right\} = (1+\Omega_\tau - \Omega_f) \cdot [1-(1-\lambda)\ln(TFPR)] \ .$$

λ remains equal to $\frac{\sigma^2_{\ln\tau}}{\sigma^2_{\ln TFPR}}$; but now $\sigma^2_{\ln TFPR}$ reflects both measurement errors, $\sigma^2_{\ln\frac{\widehat{R}I}{R\widehat{I}}}$. Here we have assumed that $\blacktriangle f/I$, as well as ΔA and $\Delta\tau$, are $i.i.d.$[19] As before, predicted plant $\ln(\tau)$ is equal to λ times its $\ln(TFPR)$.

Our specification for stationary $\ln(\tau_i)$ continues to have the form

$$E\left\{\widehat{\beta} \mid \ln(TFPR)\right\} = \left[\Psi + \Lambda(\ln(TFPR))^2\right] \cdot [1-(1-\lambda)\ln(TFPR)] \ .$$

But now $\Lambda(\ln(TFPR))^2$ captures $E\left\{-\widehat{\Omega}_\tau + \widehat{\Omega}_f \mid \ln(TFPR)\right\}$. Regression to the mean

[19] This equation reflects approximating $\frac{\widehat{R}I - R\widehat{I}}{\widehat{R}I}$ by $\ln\left(\frac{\widehat{R}I}{R\widehat{I}}\right)$.

acts to increase $-\widehat{\Omega}_\tau$ and $\widehat{\Omega}_f$ at extreme values, respectively, for $\ln(\tau_i)$ and $\frac{f_i}{\widehat{I}_i}$. These rationalize a negative value for parameter Λ.

5.2. Estimates for the U.S. and India

Our baseline estimating equation takes the form

$$\Delta\widehat{R}_i = \Phi \cdot \ln(TFPR_i) + \Psi \cdot \Delta\widehat{I}_i - \Psi(1-\lambda) \cdot \ln(TFPR_i) \cdot \Delta\widehat{I}_i + D_s + \xi_i. \quad (2)$$

Δ's reflect annual growth rates, and time subscripts remain implicit. $\ln(TFPR_i)$ is the Tornqvist average for the current and previous years that span the changes in inputs and revenue. D_s (D_{st} fully enumerated) denotes a full set of sector-year fixed effects. As discussed above, $\lambda = \frac{\sigma^2_{\ln\tau}}{\sigma^2_{\ln TFPR}}$ and $\Psi = 1 + \Omega_\tau - \Omega_f$. We allow parameter Φ so that the interaction variable $\ln(TFPR_{it}) \cdot \Delta\widehat{I}_{it}$ has a clear interpretation. But we have no anticipated sign for Φ, given that $\ln(TFPR_{it})$ is measured by its Tornqvist average. Estimation is by GMM, with observations weighted by their gross output shares. Extreme values for the data series $\Delta\widehat{R}_{it}$ and $\Delta\widehat{I}_{it}$ are winsorized at the 1% tails.

Results are given in Table 3 for both Indian and U.S. manufacturing. Looking first at India, we see that $\widehat{\Psi} = 0.97$. So, evaluated at mean $\ln(TFPR)$, growth in measured inputs translates nearly one-to-one to measured revenue. But the key parameter is λ. Its estimate is well below one, at 0.55. This reflects strong predictive power of $\ln(TFPR)$ for β. The implied value for β for a plant with $\ln(TFPR)$ of 0.5 above its sector mean is only 0.74, compared to 1.19 for a plant with $\ln(TFPR)$ of 0.5 below average. The implication is that only a little over half of observed differences in $TFPR$ reflect actual differences in τ's.

Results for the U.S. are even more dramatic. λ is only 0.23, suggesting that more than three quarters of plant dispersion in $TFPR$ in the U.S. reflects mismeasurement rather than true differences in τ. Not surprisingly, we find below that this sharply reduces productivity losses from misallocation.

Given the volatility over time for the raw measures of misallocation, especially for the United States, we ask whether our approach yields differing results when applied to subperiods. We break the 1985 to 2011 Indian data into three periods, with results

Table 3: Baseline Estimates for U.S. and India

	India 1985–2011	U.S. 1978–2007
$\widehat{\Phi}$	0.052	0.053
	(0.005)	(0.002)
$\widehat{\Psi}$	0.967	0.794
	(0.005)	(0.004)
$\widehat{\lambda}$	**0.547**	**0.229**
	(0.035)	**(0.026)**
Observations	277,239	1,141,000

Note: Estimates are from specification 2 using the Indian ASI and U.S. ASM. An observation is a plant-year. The dependent variable is revenue growth. $\widehat{\Phi}$ is the coefficient on *TFPR*, $\widehat{\Psi}$ on composite input growth, and $1-\widehat{\lambda}$ on the product of the two. Revenue growth and composite input growth are winsorized at the 1% level. Observations are weighted by the plant's Tornqvist share of aggregate output. Standard errors are clustered at the plant-level.

Table 4: Indian Baseline Estimates in Windows

	1985–1993	1994–2001	2002–2011
$\widehat{\lambda}$	**0.562**	**0.510**	**0.576**
	(0.050)	**(0.080)**	**(0.027)**
Observations	87,777	73,657	115,895

Note: Estimates of $\widehat{\lambda}$ are from specification 2 for three separate periods covered by the Indian ASI. An observation is a plant-year. The dependent variable is revenue growth. Revenue growth and composite input growth are winsorized at the 1% level. Observations are weighted by the plant's Tornqvist share of aggregate output. Standard errors are clustered at the plant-level.

given in Table 4. We have roughly four times as many plant-year observations from U.S. data for 1978 to 2007, so we break the U.S. results into six periods in Table 5. The Indian results are fairly similar across subperiods, but do exhibit a higher ratio of measurement error (lower $\widehat{\lambda}$) for 1994 to 2001, which has he greatest dispersion in $TFPR$. For the U.S., $\widehat{\lambda}$ distinctly declines in the latter part of the sample when measured dispersion and misallocation climbs upward (Figure 2).

In Figure 4 we provide a plot of $\ln(\blacktriangle\widehat{R}_i/\blacktriangle\widehat{I}_i)$ versus $\ln(TFPR_i)$ for the Indian data. (A plot for U.S. data will be added.) The data are broken into percentiles by $TFPR$, with the average value for $\blacktriangle\widehat{R}_i/\blacktriangle\widehat{I}_i$ calculated by weighting each observation by its absolute value for $\blacktriangle\widehat{I}_i$. Under no measurement error we should see (on the $\ln$ scale) a slope of one, but zero if differences in $TFPR$ are entirely illusory. The realized slope is in between, as we should expect given the estimate of $\widehat{\lambda} = 0.55$ for India. The relationship is quite linear over much of the data. But it clearly lies below the fitted line for extreme values of $TFPR_i$, both negative and positive extremes with the exception of the very highest percentile. Our derivations of β_i anticipated this relationship. Because extreme values of $\ln(TFPR)$ suggest extreme values for $\ln(\tau)$ and/or $\ln(\widehat{I}/I)$, it will also imply greater volatility for these variables, assuming they are stationary. This implies lower values for $(1 + \Omega_\tau - \Omega_f)$ and for β.

Table 5: U.S. Baseline Estimates in Windows

	1978–1982	1983–1987	1988–1992	1993–1997	1998–2002	2003–2007
$\widehat{\lambda}$	**0.358**	**0.336**	**0.326**	**0.326**	**0.192**	**0.095**
	(0.027)	**(0.034)**	**(0.031)**	**(0.037)**	**(0.032)**	**(0.070)**
Observations	143,000	146,000	160,000	164,000	158,000	157,000

Note: Estimates of $\widehat{\lambda}$ are from specification 2 for six separate periods covered by the U.S. ASM. An observation is a plant-year. The dependent variable is revenue growth. Revenue growth and composite input growth are winsorized at the 1% level. Observations are weighted by the plant's Tornqvist share of aggregate output. Standard errors are clustered at the plant-level.

We therefore turn to our generalized specification, which takes the form

$$\begin{aligned}\Delta\widehat{R}_i = \; & \Phi \cdot \ln(TFPR_i) + \Psi \cdot \Delta\widehat{I}_i - \Psi(1-\lambda) \cdot \ln(TFPR_i) \cdot \Delta\widehat{I}_i \\ & + \Gamma \cdot (\ln(TFPR_i))^2 + \Lambda(1-\lambda) \cdot (\ln(TFPR_i))^2 \cdot \Delta\widehat{I}_i \\ & + \Upsilon \cdot (\ln(TFPR_i))^3 + \Lambda(1-\lambda) \cdot (\ln(TFPR_i))^3 \cdot \Delta\widehat{I}_i + D_s + \xi_i. \end{aligned} \tag{3}$$

Results are given in Table 6 for India and Table 7 for the U.S. For India, allowing for mean reversion reduces $\widehat{\lambda}$ very modestly. When estimated separately on the three subperiods, $\widehat{\lambda}$ is reduced in all periods, but by slightly more, from 0.51 to 0.47, in the middle period with the most dispersion in $TFPR$.

Turning to Table 7 for the U.S., we see that generalizing the specification makes a considerably bigger difference, but only for the later sample years. For 1998–2002, $\widehat{\lambda}$ goes from 0.19, under the standard specification, to 0.13. For 2003–2007, $\widehat{\lambda}$ is reduced from 0.10 all the way down to 0.02, implying a negligible mapping of $TFPR$ to distortions in these later years.

5.3. Measurement Error in Input Ratios

So far we have considered measurement errors in labor, capital, and intermediates of the same proportion. But part of the calculated misallocation in Figure 2 comes from dispersion in relative inputs, not dispersion in $TFPR$. Under the assumption that

Table 6: Indian Estimates Allowing for Mean Reversion

	All Years	1985-1993	1994-2001	2002-2011
Baseline $\widehat{\lambda}$	0.547	0.562	0.510	0.576
	(0.035)	(0.050)	(0.080)	(0.027)
$\widehat{\lambda}$ with mean reversion	**0.520**	**0.547**	**0.465**	**0.562**
	(0.041)	**(0.060)**	**(0.090)**	**(0.029)**
Observations	277,239	87,777	73,657	115,895

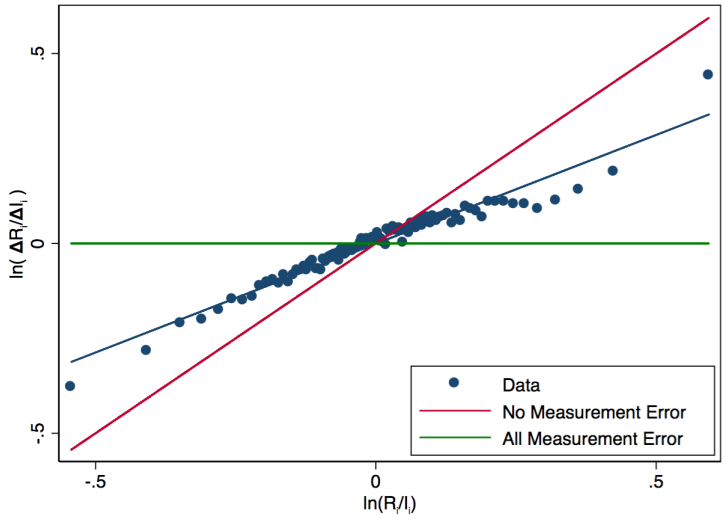
Estimates of $\widehat{\lambda}$ are from specifications 2 and 3 for three separate periods covered by the Indian ASI. An observation is a plant-year. The dependent variable is revenue growth. Revenue growth and composite input growth are winsorized at the 1% level. Observations are weighted by the plant's Tornqvist share of aggregate output. Standard errors are clustered at the plant-level.

Table 7: U.S. Estimates Allowing for Mean Reversion

	All Years	1978–1982	1983–1987	1988–1992	1993–1997	1998-2002	2003-2007
Baseline $\widehat{\lambda}$	.229	0.358	0.336	0.326	0.326	0.192	0.095
	(.026)	(0.027)	(0.034)	(0.031)	(0.037)	(0.032)	(0.070)
$\widehat{\lambda}$ with mean reversion	**0.205**	**0.371**	**0.312**	**0.318**	**0.318**	**0.129**	**0.020**
	(0.018)	**(0.029)**	**(0.037)**	**(0.033)**	**(0.038)**	**(0.041)**	**(0.054)**
Observations	1,141,000	143,000	146,000	160,000	164,000	158,000	157,000

Note: Estimates of $\widehat{\lambda}$ are from specifications 2 and 3 for three separate periods covered by the Indian ASI. An observation is a plant-year. The dependent variable is revenue growth. Revenue growth and composite input growth are winsorized at the 1% level. Observations are weighted by the plant's Tornqvist share of aggregate output. Standard errors are clustered at the plant-level.

Figure 4: Measured Marginal Products vs TFPR: India



Source: The Indian Annual Survey of Industries (ASI), using the years 1985 to 2011. The blue line in the figure is the line of best fit from a regression of $\blacktriangle\widehat{R}_i/\blacktriangle\widehat{I}_i$ on $\ln(\widehat{R}_i/\widehat{I}_i)$. The blue dots plot a non-parametric version of this regression, where each dot corresponds to one of 100 centiles of $\ln(\widehat{R}_i/\widehat{I}_i)$. An observation in the regression is a plant-year. Sector-year fixed effects are removed from both the right-hand side and left-hand side variables. Observations are weighted by the absolute value of composite input growth (winsorized at the 1% level).

input elasticities are common across plants, input shares should not differ unless the mix is distorted across plants. So dispersion in input mix is treated as misallocation.[20] But, if spending on inputs is subject to mismeasure, it is natural that those errors could affect input ratios.

We pursue an approach, similar in spirit to that above for $TFPR$, to gauge if dispersion in input ratios reflects mismeasurement. The logic is that, if total inputs expand, then this acts to reduce the mismeasure of the ratio of inputs. The key assumption here is that measurement errors in are additive to true inputs. To the extent errors are instead proportional, then they will go undetected by our procedure. For this reason, our approach can be viewed as conservative in its estimate of the role of measurement error in explaining dispersion in the ratio of inputs across plants.[21]

[20]Much of the literature on misallocation has focused on distortions to the capital-labor ratio. Examples include Midrigan and Xu (2014), Asker et al. (2014), Gopinath et al. (2016), Garicano et al. (2016), and Kehrig and Vincent (2017).

[21]Our procedure also fails to detect the extent that input elasticities differ across plants in a sector, violating the assumption of common elasticities. This is a further reason to view our procedure as conservative, that is, conservative in that the the amount of misallocation still

The growth rate in the measured ratio of capital to labor inputs is given by

$$\Delta\frac{\widehat{K}_i}{\widehat{L}_i} = \frac{\left(\frac{K_i}{\widehat{K}_i}\cdot\frac{L_i}{\widehat{L}_i}\right)\Delta Z_i - \left[\left(\frac{\widehat{K}_i-K_i}{K_i}\right)-\left(\frac{\widehat{L}_i-L_i}{L_i}\right)\right]\Delta\widehat{V}_i}{1-\alpha\left(\frac{\widehat{K}_i-K_i}{K_i}\right)-(1-\alpha)\left(\frac{\widehat{L}_i-L_i}{L_i}\right)},$$

with

$$\Delta Z_i = \Delta\tau_{L_i} - \Delta\tau_{K_i} + \frac{\blacktriangle f_{K_i}}{\widehat{K}_i} - \frac{\blacktriangle f_{L_i}}{\widehat{L}_i}.$$

$\Delta\widehat{V}_i$ denotes growth in value added, as measured by $\alpha\Delta\widehat{K}_i + (1-\alpha)\Delta\widehat{L}_i$. $\Delta\tau_K$ and $\Delta\tau_L$ denote respective changes in capital and labor distortions; and $\blacktriangle f_K$ and $\blacktriangle f_L$ are absolute changes in the inputs' measurement errors.

The goal is to isolate the role of $\left(\frac{\widehat{K}_i-K_i}{K_i}\right)-\left(\frac{\widehat{L}_i-L_i}{L_i}\right)$ in differences in $\ln\left(\frac{\widehat{K}_i}{\widehat{L}_i}\right)$. We proceed by regressing $\Delta\widehat{K}_i - \Delta\widehat{L}_i$ on $\Delta\widehat{V}_i$, as well as $\Delta\widehat{V}_i$ interacted with $\ln\left(\frac{\widehat{K}_i}{\widehat{L}_i}\right)$. If we assume that ΔZ_i is orthogonal to $\left(\frac{\widehat{K}_i-K_i}{K_i}\right)-\left(\frac{\widehat{L}_i-L_i}{L_i}\right)$, then this provides a test for the role of measurement error in $\ln\left(\frac{\widehat{K}_i}{\widehat{L}_i}\right)$.[22] The expected coefficient from regressing $\Delta\widehat{K}_i - \Delta\widehat{L}_i$ on $\Delta\widehat{V}_i$, call it ν is then

$$\begin{aligned} E\left\{\nu \mid \ln\left(\frac{\widehat{K}}{\widehat{L}}\right)\right\} &= \Pi - E\left\{\frac{\left(\frac{\widehat{K}-K}{K}\right)-\left(\frac{\widehat{L}-L}{L}\right)}{1-\alpha\left(\frac{\widehat{K}-K}{K}\right)-(1-\alpha)\left(\frac{\widehat{L}-L}{L}\right)} \mid \ln\left(\frac{\widehat{K}}{\widehat{L}}\right)\right\} \\ &\approx \Pi - (1-\lambda_{KL})\ln\left(\frac{\widehat{K}}{\widehat{L}}\right). \end{aligned}$$

The sign of the intercept Π is dictated by the covariance of $\Delta\widehat{V}_i$ and ΔZ_i. λ_{KL} denotes the fraction of dispersion $\ln\left(\frac{\widehat{K}}{\widehat{L}}\right)$ due to dispersion in $\ln\left(\frac{K}{L}\right)$, not from measurement error.[23] If there is no measurement error in the *ratio* of inputs, then $\lambda_{KL} = 1$. If the true ratio $\frac{K_i}{L_i}$ and measurement error in the ratio are independent, then we have that

attributed to differences in input ratios would be overly generous.

[22]This assumes that changes in relative measurement errors are orthogonal to the level of relative measurement errors. For instance, if $\frac{\blacktriangle f_{K_i}}{\widehat{K}_i}$ and $\frac{\blacktriangle f_{L_i}}{\widehat{L}_i}$ are $i.i.d.$, then this would hold true.

[23]The approximately equal reflects that $\frac{\left(\frac{\widehat{K}-K}{K}\right)-\left(\frac{\widehat{L}-L}{L}\right)}{1-\alpha\left(\frac{\widehat{K}-K}{K}\right)-(1-\alpha)\left(\frac{\widehat{L}-L}{L}\right)}$ and $\ln\left(\frac{\widehat{K}}{\widehat{L}}\right)$ are equal to a linear approximation near $\left(\frac{\widehat{K}-K}{K}\right)=0$, $\left(\frac{\widehat{L}-L}{L}\right)=0$. The linear projection on $\ln\left(\frac{\widehat{K}}{\widehat{L}}\right)$ reflects an assumption that true $\ln\left(\frac{\widehat{K}}{\widehat{L}}\right)$ and its measurement error are normally distributed.

$\sigma^2_{\ln \frac{K}{L}} = \lambda_{\frac{K}{L}} \sigma^2_{\ln \frac{\widehat{K}}{\widehat{L}}}$.

We proceed in the same manner to estimate measurement error in the ratio of value added to intermediates, $\frac{\widehat{V}_i}{\widehat{X}_i}$. We refer to the corresponding λ parameter as $\lambda_{\frac{V}{X}}$. We relegate those derivations to an appendix (to be added).

The equation for estimating $\lambda_{\frac{K}{L}}$ takes the form

$$\Delta \frac{\widehat{K}_i}{\widehat{L}_i} = \Phi \cdot \ln \left(\frac{\widehat{K}_i}{\widehat{L}_i} \right) + \Pi \cdot \Delta \widehat{V}_i - (1 - \lambda_{KL}) \cdot \ln \left(\frac{\widehat{K}_i}{\widehat{L}_i} \right) + D_s + \xi_i \tag{4}$$

The equation for estimating $\lambda_{\frac{V}{X}}$ takes the same form, but value-added and intermediates take the place of capital and labor, while growth in measured gross output replaces $\Delta \widehat{V}_i$.[24]

Results are presented for Indian data in Table 8 and for U.S. in Table 9 . The estimates of λ, for $TFPR$ differences, are repeated for comparison. Estimates for $\lambda_{\frac{K}{L}}$ and $\lambda_{\frac{V}{X}}$ are much closer to one. Estimated for India for 1985 to 2011, these are 0.93 and 0.91 respectively; and across subperiods both parameters remain near, or above, 0.9. For the United States $\lambda_{\frac{K}{L}}$, estimated for the full sample, is 0.80; and it is 0.78 or above for all six subperiods. $\lambda_{\frac{V}{X}}$ is even higher: 0.84 for the full sample and 0.81, or higher, for all subperiods. Because our estimates for $\lambda_{\frac{K}{L}}$ and $\lambda_{\frac{V}{X}}$ are much closer to one than those for λ, adjusting for errors in input *ratios* plays a fairly minor role in our calculations of misallocation that follow.

[24]Parameters are estimated by GMM, with observations weighted by gross output shares. Extreme values for series $\Delta \frac{\widehat{K}_i}{\widehat{L}_i}$ and $\Delta \widehat{V}_i$ are winsorized at the 1 percent tails in estimating $\lambda_{\frac{K}{L}}$; as are $\Delta \frac{\widehat{V}_i}{\widehat{X}_i}$ and the growth rate in gross output in estimating $\lambda_{\frac{V}{X}}$.

Table 8: Indian Estimates with Relative Measurement Error

	All Years	1985-1993	1994-2001	2002-2011
$\widehat{\lambda}$ with mean reversion	0.520	0.547	0.465	0.562
	(0.041)	(0.060)	(0.090)	(0.029)
$\widehat{\lambda}_{KL}$	**0.927**	**0.910**	**0.888**	**0.976**
	(0.022)	**(0.035)**	**(0.039)**	**(0.033)**
$\widehat{\lambda}_{VX}$	**0.912**	**0.895**	**0.902**	**0.928**
	(0.011)	**(0.014)**	**(0.019)**	**(0.020)**
Observations	277,239	87,777	73,657	115,895

Estimates of $\widehat{\lambda}$ are from specification 3; those of $\widehat{\lambda}_{KL}$ and $\widehat{\lambda}_{VX}$ from specification 4. An observation is a plant-year. The dependent variable is revenue growth. Revenue growth and composite input growth in the ASI are winsorized at the 1% level. Observations are weighted by the plant's Tornqvist share of aggregate output. Standard errors are clustered at the plant-level.

Table 9: U.S. Estimates with Relative Measurement Error

	All Years	1978–1982	1983–1987	1988–1992	1993–1997	1998-2002	2003-2007
$\widehat{\lambda}$ with mean reversion	0.205	0.371	0.312	0.318	0.318	0.129	0.020
	(0.018)	(0.029)	(0.037)	(0.033)	(0.038)	(0.041)	(0.054)
$\widehat{\lambda}_{KL}$	**0.797**	**0.822**	**0.777**	**0.815**	**0.780**	**0.777**	**0.831**
	(0.009)	**(0.020)**	**(0.016)**	**(0.017)**	**(0.026)**	**(0.030)**	**(0.026)**
$\widehat{\lambda}_{VX}$	**0.838**	**0.884**	**0.883**	**0.840**	**0.821**	**0.839**	**0.811**
	(0.006)	**(0.010)**	**(0.011)**	**(0.011)**	**(0.018)**	**(0.014)**	**(0.021)**
Observations	1,141,000	143,000	146,000	160,000	164,000	158,000	157,000

Estimates of $\widehat{\lambda}$ are from specification 3; those of $\widehat{\lambda}_{KL}$ and $\widehat{\lambda}_{VX}$ from specification 4. An observation is a plant-year. The dependent variable is revenue growth. Revenue growth and composite input growth in the ASM are winsorized at the 1% level. Observations are weighted by the plant's Tornqvist share of aggregate output. Standard errors are clustered at the plant-level.

6. Revisiting Misallocation

We now compare the "raw" measures of allocative efficiency for Indian and U.S. manufacturing to our estimates purging the impact of measurement error. We first present results maintaining that measurement errors are common across inputs–we refer to this as the common correction. We then additionally correct for errors affecting dispersion in input ratios.

To get at dispersion in τ_i, our first step is to take plants' $\ln(TFPR)$'s, then scale differences by $\widehat{\lambda}$. But this does not capture the entirety of distortions across plants because, in the presence of measurement error, there is a component of dispersion in τ_i's that is orthogonal to $\ln(TFPR)$. For this reason, we build an alternative measure of firm distortion, $\widetilde{TFPR}_i$, by adding to the scaled variable $\widehat{\lambda} \cdot \ln(TFPR_i)$ an independently drawn random variable, ϵ_i. ϵ_i is drawn from a normal distribution so that it yields $\sigma^2_{ln(\widetilde{TFPR})} = \widehat{\lambda} \cdot \sigma^2_{ln(TFPR)}$.

$$\widetilde{TFPR}_i \propto \exp\left(\widehat{\lambda} \cdot \ln(TFPR_i) + \epsilon_i\right)$$

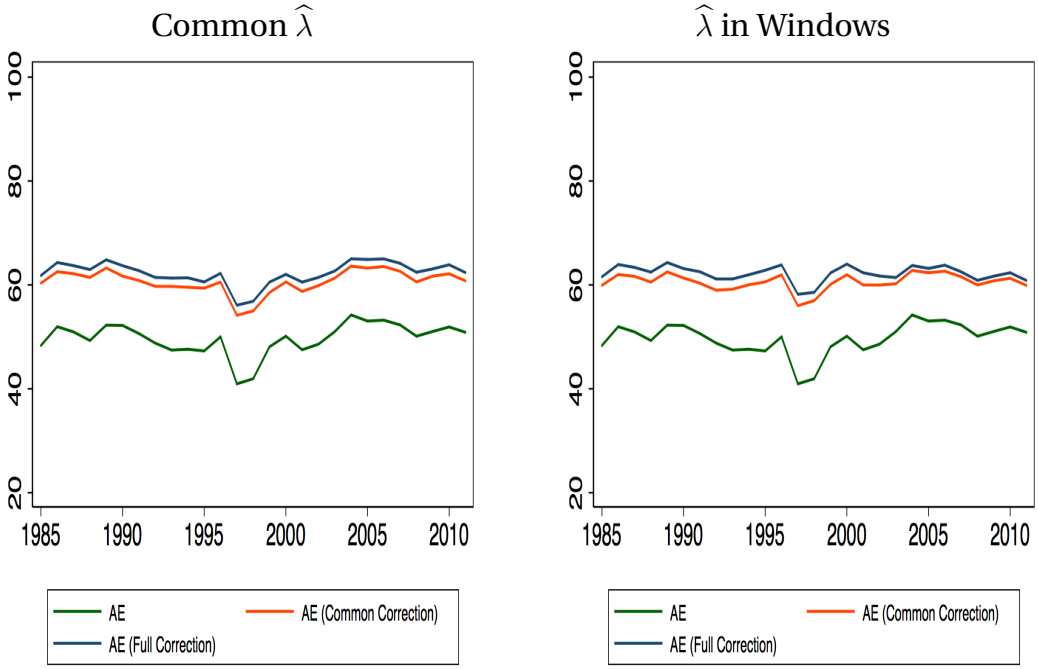
$$\text{where} \qquad \epsilon_i \sim N\left(0, (\widehat{\lambda} - \widehat{\lambda}^2)\sigma^2_{\ln(TFPR)}\right).$$

Our estimates for $\widehat{\lambda}$ are those given in Table 6 (India) and Table 7 (U.S.) that allow for mean reversion in measurement error and in τ's.

We make comparable corrections to treat the presence of relative measurement error across intermediates, capital and labor.

We display the impact of these corrections on implied allocative efficiency in Figures 5 and 6, respectively, for India and the United States. Looking at Figure 5, the left panel imposes a common $\widehat{\lambda}$, while the right allows for separate $\widehat{\lambda}$'s across the three time periods. Given the similarity of the results, we focus on those on the right. The correction greatly increases Indian allocative efficiency. This is particularly so for the late 1990's when misallocation, based on raw $TFPR$, is especially high. Table 10 reports the magnitudes employing separate estimates of λ by time period. The common correction increases allocative efficiency from 49 to 61 percent, thereby reducing the potential gains from reallocation from 102 to 65 percent. Correcting for error in input ratios has

Figure 5: Allocative Efficiency in India



Source: Indian ASI. The figures show uncorrected and corrected allocative efficiency (AE) for the years 1985 to 2011. The left panel shows corrected AE when a common estimate of $\widehat{\lambda}$ is used over the whole time frame. The right panel shows corrected AE when $\widehat{\lambda}$ is allowed to vary across three windows. Average uncorrected AE is 49% while average corrected AE (using the full correction and $\widehat{\lambda}$ in windows) is 62%.

a much smaller effect, taking the potential gains down further to 61 percent. Relative to the standard treatment of no measurement error, potential gains from reallocation are reduced by 40 percent.

Still focusing on India, we see from Figure 5 and Table 10 that correcting greatly reduces the implied volatility of misallocation over time. The standard deviation of potential gains is reduced by nearly three quarters, from 13.7 to only 4.0 percent.

Turning to the United States, Figure 6, we see an even far greater impact from correcting for measurement error. Again the left panel imposes a common $\widehat{\lambda}$, while the right allows for separate $\widehat{\lambda}$'s by 5-year period. Regardless, the correction eliminates the bulk of potential gains from reallocation. Despite a common $\widehat{\lambda}$ in the left panel, most of the apparent downward trend in allocative efficiency is eliminated; in the right panel, with separate $\widehat{\lambda}$'s, that trend is eliminated entirely.

Table 10 reports magnitudes. The common correction reduces potential gains from 96 percent all the way down to 28 percent. Correcting as well for error in input ratios

takes those potential gains down still further to 24 percent. Thus, relative to allowing for no measurement error, potential gains are reduced by three quarters.

Just as striking is the impact on the volatility of U.S. gains from reallocation. The correction not only removes any upward trend in the gains, it also moderates its higher frequency vagaries. As a result, the volatility of that time series is reduced nearly completely, with its standard deviation going from 54 percent to only 3 percent.

Lastly, Figure 7 displays the implied differential in allocative efficiency between the United States and India. Without correcting, the U.S. averages about a 20 percent advantage in allocative efficiency from 1985 to the late 1990's, though the actual advantage is fairly volatile. Then, over the last 10 years, U.S. efficiency collapses absolutely and relative to India. By the last several years of data U.S. efficiency is only 60 percent of that for India.

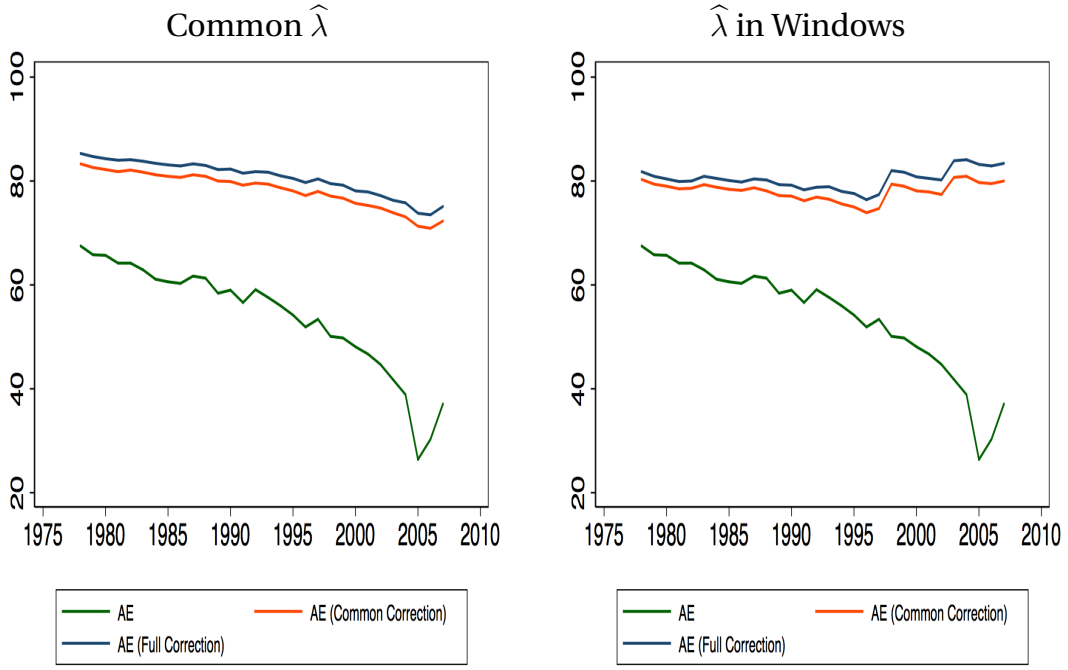
Our corrected series, however, looks entirely different. The U.S. advantage is higher, averaging about 35 percent, compared to only about 5 percent uncorrected. Furthermore, that advantage remains stably at 30 to 40 percent throughout the sample period.

Table 10: Uncorrected vs. Corrected Gains from Reallocation

	India 1985–2011		U.S. 1978–2007	
	Mean	S.D.	Mean	S.D.
Uncorrected Gains	102.0%	13.7%	95.6%	53.5%
Corrected Gains (Common)	65.2%	4.5%	28.1%	2.9%
Corrected Gains (Common & Relative)	60.8%	4.0%	24.4%	3.0%
Shrinkage	40%	71%	74%	94%

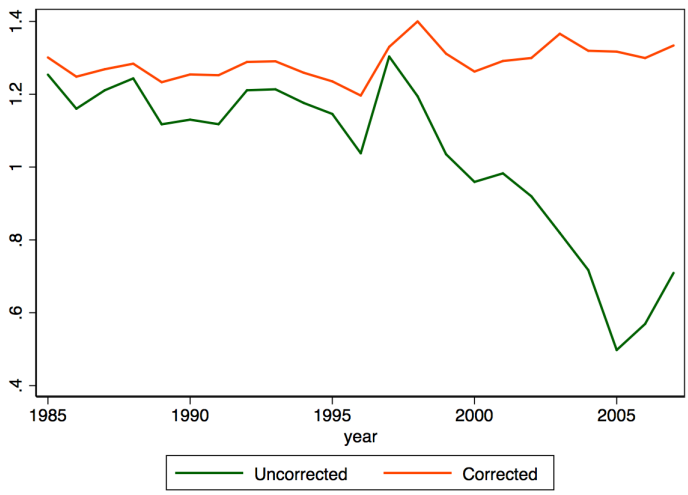
Source: Indian ASI (1985 to 2011) and U.S. ASM (1978 to 2007).

Figure 6: Allocative Efficiency in the U.S.



Source: U.S. ASM. The figures show uncorrected and corrected allocative efficiency (AE) for the years 1978 to 2007. The left panel shows corrected AE when a common estimate of $\widehat{\lambda}$ is used over the whole time frame. The right panel shows corrected AE when $\widehat{\lambda}$ is allowed to vary across three windows. Average uncorrected AE is 54% while average corrected AE (using the full correction and $\widehat{\lambda}$ in windows) is 80%.

Figure 7: Allocative Efficiency: U.S. Relative to India



Source: Indian Annual Survey of Industries (ASI) and U.S. Annual Survey of Manufactures (ASM). The figure plots the uncorrected and corrected ratio of U.S. allocative efficiency to Indian allocative efficiency for the years 1985 to 2007 (years in which the datasets overlap). The corrected allocative efficiency estimates are those using the full correction with $\widehat{\lambda}$ in windows.

7. Conclusion

We propose a way to estimate the true dispersion of marginal products across plants in the presence of additive measurement error in revenue and inputs. Our method exploits the idea that there is additional information on true marginal products afforded by panel data. Essentially, we project revenue growth on input growth, revenue productivity, and input growth *interacted* with revenue productivity. The interaction term should be zero if the level of revenue productivity reflects true differences in marginal products. In contrast, the interaction term should be inversely negative if revenue productivity is a spurious indicator of true marginal products. Our key identifying assumption here is that the measurement error is orthogonal to the true marginal product.

We implemented our method on data from the Indian *Annual Survey of Industries* from 1985–2011 and the US. *Annual Survey of Manufacturing* from 1978–2007. In India, we estimate that true Marginal products are $\frac{1}{2}$ as dispersed as the average products. The

potential gains from reallocation are reduced by $\frac{2}{5}$, and the time time-series volatility of such gains is shaved by $\frac{2}{3}$. In the U.S., our correction eliminates a severe downward trend in allocative efficiency. Instead of cutting U.S. manufacturing productivity in half (relative to what it otherwise would have done), allocative efficiency looks stable in the U.S. Higher allocative efficiency in the U.S. appears to consistently contribute to 30-40% higher productivity than in India for the years our samples overlap.

We hope our method provides a useful diagnostic and correction for measurement errors that can be applied whenever researchers have access to panel data on plants and firms. Our findings leave many open questions for future research. For one, measurement error seemed to worsen considerably over time in the U.S. ASM. What might be the source? And, even after our correction there seems to be ample misallocation in the U.S. and India. Is this real or due to some combination of model misspecification and proportional measurement error? If it is real, can it be traced to specific government policies or market failures (e.g. markup dispersion or capital and labor market frictions)?

8. Model Appendix

8.1. Solving the Firm's Problem

Solving the representative firm's problem and normalizing the price index of the final good $P = 1$, we obtain the demand for sectoral output:

$$Q_s = \frac{1}{P_s}\theta_s Q$$

We can also obtain the demand curve facing firm i in sector s

$$P_{si} = \theta_s Q Q_s^{\frac{1-\epsilon}{\epsilon}} Q_{si}^{-\frac{1}{\epsilon}}$$

With this we can solve the heterogeneous firms' problem. We obtain the standard result that prices are a constant markup over marginal cost:

$$P_{si} = \left(\frac{\epsilon}{\epsilon - 1}\right)\frac{1}{\gamma_s^{\gamma_s}}\left[\left(\frac{r}{\alpha_s}\right)^{\alpha_s}\left(\frac{w}{1-\alpha_s}\right)^{1-\alpha_s}\right]^{\gamma_s}\left[\frac{1}{1-\gamma_s}\right]^{1-\gamma_s}\frac{1}{\tau_{si}A_{si}}$$

8.2. Aggregating to Sector-Level

Aggregating to the sector level, we can express sectoral gross output as a function of sectoral inputs and sectoral productivity A_s:

$$Q_s = A_s(K_s^{\alpha_s} L_s^{1-\alpha_s})^{\gamma_s} X_s^{1-\gamma_s}$$

where

$$A_s = \left[\sum_{i=1}^{N_{st}} A_{si}^{\epsilon-1}\left(\frac{\tau_s}{\tau_{si}}\right)^{1-\epsilon}\right]^{\frac{1}{\epsilon-1}}$$

The *average sectoral distortions* on labor is defined as follows:

$$1+\tau_s^L \equiv \left[\sum_{i=1}^{N_s} \frac{R_{si}}{R_s}\frac{1}{1+\tau_{si}^L}\right]^{-1} = \frac{\left[\sum_{i=1}^{N_s}\left[\frac{A_{si}}{\tau_{si}}\right]^{\epsilon-1}\right]}{\left[\sum_{i=1}^{N_s}\left[\frac{A_{si}}{\tau_{si}}\right]^{\epsilon-1}\frac{1}{1+\tau_{si}^L}\right]}$$

and similarly for τ_s^K and τ_s^X.

8.3. Aggregate Consumption

Aggregate value added in this model ($C = Q - X$) can be expressed as follows:

$$C = \left(\frac{\epsilon}{\epsilon-1}\right)^{\frac{\sum_s^S(1-\gamma_s)\theta_s}{\sum_s^S\gamma_s\theta_s}} \times \prod_s^S \theta_s^{\frac{\theta_s}{\sum_s^S\gamma_s\theta_s}} \times \prod_s^S \left[\left(\alpha_s^{\alpha_s}(1-\alpha_s)^{1-\alpha_s}\right)^{\gamma_s}\gamma_s^{\gamma_s}(1-\gamma_s)^{1-\gamma_s}\right]^{\frac{\theta_s}{\sum_s^S\gamma_s\theta_s}} \times$$
$$\prod_s^S\left[\frac{\tau}{\tau_s}\right]^{\frac{\theta_s}{\sum_s^S\gamma_s\theta_s}} \times \left[1-\left(\frac{\epsilon-1}{\epsilon}\right)\frac{1}{(1+\tau^X)}\sum_s^S\theta_s(1-\gamma_s)\left(\frac{1+\tau^X}{1+\tau_s^X}\right)\right] \times \left(\frac{1}{1+\tau^X}\right)^{\frac{\sum_s^S(1-\gamma_s)\theta_s}{\sum_s^S\gamma_s\theta_s}} \times$$
$$\left(\frac{L}{\sum_s^S\left[\theta_s\gamma_s(1-\alpha_s)\left(\frac{1+\tau^L}{1+\tau_s^L}\right)\right]}\right)^{\frac{\sum_s^S(1-\alpha_s)\gamma_s\theta_s}{\sum_s^S\gamma_s\theta_s}} \times \left(\frac{K}{\sum_s^S\left[\theta_s\gamma_s\alpha_s\left(\frac{1+\tau^K}{1+\tau_s^K}\right)\right]}\right)^{\frac{\sum_s^S\alpha_s\gamma_s\theta_s}{\sum_s^S\gamma_s\theta_s}} \times$$
$$\prod_s^S A_s^{\frac{\theta_s}{\sum_s^S\gamma_s\theta_s}}$$

where

$$\tau \equiv \left[(1+\tau^L)^{1-\alpha_s}(1+\tau^K)^{\alpha_s}\right]^{\gamma_s}(1+\tau^X)^{1-\gamma_s}$$

$$\tau^L \equiv \frac{1}{\sum_i^S \frac{R_s}{Q}\frac{1}{1+\tau_s^L}}$$

and similarly for τ^K and τ^X.

It is worth noting that the exponents on the sectoral productivity term $\left(\prod_{s=1}^S A_s^{\frac{\theta_s}{\sum_{s=1}^S\gamma_s\theta_s}}\right)$ sum to > 1. This is due to the amplification effect of intermediate inputs. A 1% increase

in the productivity of each sector leads to a *greater* than 1% increase in aggregate consumption.

9. Data Appendix

The Indian plant-level dataset used is the Indian Annual Survey of Industries (ASI) for the years 1985 to 2011. This can be purchased through India's Ministry of Statistics and Programme Implementation (MOSPI).[25]. The reference period of the survey is the accounting year, which in India begins on the 1st of April and ends on the 31st of March the following year. We reference the surveys by the earlier of the two years covered.[26] The datasets used for the years 1985-1994 are 'summary' datasets as opposed to 'detailed' datasets. These are years in which in which the dataset contains only a subset of the variables available in the full survey schedule, however they contain all the variables we use in this paper. The ASI is a representative sample of plants with at least 10 workers, (20 workers for plants that don't use power). Sampling weights are provided with the data, and the sampling methodology in each year is described in more detail below.

The US plant-level dataset used is the Annual Survey of Manufacturers (ASM) for the years 1972 to 2012. The ASM is conducted annually. The ASM is a representative sample of US manufacturing plants with one or more paid employee.

The main variables we construct from both datasets in each year are: gross output, capital, labor, labor costs, intermediate inputs, and industry classification. We describe each of these variables in more detail below.

9.1. Main Variables

Labor: We construct labor as the average number of personnel in the plant over the year. Personnel include wage or salary workers, supervisory/managerial staff, administrative/custodial employees and all unpaid workers (including family members). In the 1998 and 1999 surveys, the number of unpaid workers was not asked. We adjust for this as follows: we set the number of unpaid workers for a plant in 1998(1999) as the number of unpaid workers in the same plant in 1997(2000). If the plant was not

[25]See the following link: http://mospi.nic.in/mospi_new/upload/asi/ASI_main.htm
[26]We refer to the ASI covering the accounting year 1996-1997 as the 1996 ASI.

surveyed in the preceding(following) year, we set the number of unpaid workers equal to the average number of unpaid workers in that industry in the preceding(following) year.[27]

Labor Cost: We construct labor costs as total payments to labor over the course of the year. These payments include wages and salaries, bonuses, contributions to old-age pension funds (and other funds), and all welfare expenses.[28]

Capital: This is constructed as the average of the opening and closing book value of fixed assets (net of depreciation). These include all types of assets deployed for production and transportation, as well as living or recreational facilities (hospitals, schools, etc.) for factory personnel. It excludes intangible assets.

Intermediates: We construct intermediates as the sum of the value of materials consumed, fuels consumed and other intermediate expenses. Other intermediate expenses include repair and maintenance costs (plant/machinery, building, etc...), costs of contract and commission work, operating expenses (freight and transportation charges, taxes paid), non-operating expenses (communication, accounting, advertising), and insurance charges.

Gross Output: We construct gross output as the gross value of products sold plus all other sources of revenue. The gross value of products sold includes distribution expenses, as well as taxes and subsidies. Other sources of revenue include the value of electricity sold, the value of own construction, the value of resales, the value of additions to the stock of finished goods and semi-finished goods, as well as receipts from industrial or non-industrial services rendered (e.g. contract or commission work).

[27] Rounded to the nearest whole number.

[28] Included in these costs are social security charges such as employees' state insurance, compensation for work injuries, occupational diseases, maternity benefits, retrenchment and lay-off benefits. Also included are group benefits like direct expenditure on maternity, creches, canteen facilities, educational, cultural and recreational facilities, grants to trade unions, and co-operative stores meant for employees.

9.2. Deflators & Sectoral Classifications:

Deflators: We construct a yearly capital deflator from a table of gross capital formation in current and constant prices, available from the Reserve Bank of India (RBI) here: https://www.rbi.org.in/scripts/PublicationsView.aspx?id=15134. The underlying data for our gross output deflators are three monthly wholesale price index series from the Indian Office of the Economic Adviser. The WPI series can be downloaded here: http://eaindustry.nic.in/home.asp.[29] We construct our gross output deflators using concordances from the WPI product-level to the NIC-1987 sector-level, and from the NIC-1987 sector-level to our harmonized sector-level.[30]

Sectoral Classification We use official NIC concordances from MOSPI to create a single industrial classification that is consistent between 1985 and 2011. We match 4-digit NIC-1970 sectors to 3-digit NIC-1987 sectors, 4-digit NIC-2008 sectors to NIC-2004 sectors, and 4-digit NIC-2004 sectors to 4-digit NIC-1998 sectors. We then consolidate a number of 3-digit NIC-1998 sectors and match 3-digit NIC-1987 sectors to the consolidated 3-digit NIC-1998 sectors. This creates our harmonized sector classification of 52 manufacturing sectors.[31]

9.3. Cleaning Steps

Table 11 summarizes the different cleaning steps involved in constructing our final datasets for both India and the U.S.

9.4. Construction of Panel

Plants fall into two categories: *Census* and *Sample*. *Census* plants consist of plants over a minimum size threshold, as well as all plants in 12 of the industrially 'backwards' states. Census plants are surveyed every year. *Sample* plants are sampled at random every year within each state $\times$ 3-digit industry group. Using permanent plant identifiers provided in the dataset, we can therefore construct a panel following *Census* plants, as

[29] The three series respectively cover the years 1981-2000, 2000-2010 and 2005-2012.

[30] We obtain the former of these concordances from the ACWHO (2015) replication files.

[31] Note that there are 276 3-digit NIC-1987 manufacturing sectors and 97 (unconsolidated) 3-digit NIC-1998 manufacturing sectors.

Table 11: Data Cleaning Steps for U.S. and India

		Indian ASI	U.S. ASM
Step	Cleaning	Remaining Obs	Remaining Obs
1	Starting sample of plant-years	1,159,641	1,767,000
2	Missing no key variables	924,547	1,589,000
3	Common Sector Concordance	899,793	1523,000
4	Trimming extreme TFPR & TFPQ	844,875	1,428,000

well as *Sample* plants that happen to be surveyed in adjacent years. There are a number of breaks in the coding of the permanent plant identifiers between the years 1986-1987, 1988-1989, and 2007-2008. Our panel therefore consists of 4 sub-periods across which we can't link plants: 1985-1986, 1987-1988, 1989-2007, and 2008-2011. There have been concerns reported by the ASI data processing agency regarding the reliability of the permanent plant identifiers prior to 1998. In order to verify the quality of the permanent plant identifiers, we examine whether reported age is consistent across survey years for our panel plants.[32] In Figure 8 we show the share of panel plants that report their age as exactly one year less than they reported it in the following year. This share varies between 8% and 18%, but there is no evidence of more inconsistent reporting prior to 1998.[33]

[32]The variable we use is 'year of initial incorporation', which was not used in constructing the permanent plant identifiers. Our results are therefore not a statistical artifact.

[33]The dashed lines are missing years due to breaks in the coding of permanent plant identifiers.

Figure 8: Percentage of Plants with Inconsistently Reported Age

9.5. Changes in ASI Sampling Methodology

Period	Census Sector	Sample Sector
1985-1986	12 less industrially developed states, 50 or more workers with power, 100 or more workers without power, industries with fewer than 50 plants in all of India, electricity sector	Stratified within state $\times$ 3-digit industry (NIC-70), 50% samples of remaining non-Census plants in alternate years
1987-1996	12 less industrially developed states, 100 or more workers (with or without power), all joint returns, all plants within state $\times$ 4-digit industry if $<$ 4 plants, all plants within state $\times$ 3-digit industry if $<$ 20 plants, electricity sector	Stratified within state $\times$ 3-digit industry (NIC-87), minimum sample of 20 plants within strata, otherwise 1/3 of plants sampled
1997	12 less industrially developed states, plants with $>$ 200 workers, 'significant units' with $<$ 200 workers but contributed highly to value of output between 1993-1995, public sector undertakings, electricity sector	Stratified within state $\times$ 3-digit industry (NIC-87), minimum of 4 plants sampled per stratum
1998	Complete enumeration states, plants with $>$ 200 workers, all joint returns, electricity sector omitted	Stratified within state $\times$ 4-digit industry (NIC-98), minimum of 8 plants per stratum
1999-2003	Complete enumeration states, plants with $\geq$ 100 or more workers, all joint returns	Stratified within state $\times$ 4-digit industry (NIC-98), minimum of 8 plants per stratum, exceptions:
2004-2006	6 less industrially developed states, 100 or more workers, all joint returns, all plants within state $\times$ 4-digit industry with $<$ 4 units	Stratified within state $\times$ 4-digit industry, 20% sampling, minimum of 4 plants
2007	5 less industrially developed states, 100 or more workers, all joint returns, all plants within state $\times$ 4-digit industry with $<$ 6 units	Stratified within state $\times$ 4-digit industry, minimum 6 plants, 12% sampling fraction: exceptions
2008-2011	6 less industrially developed states, 100 or more employees, all joint returns, all plants within state $\times$ 4-digit industry with $<$ 4 units	Stratified within district $\times$ 4-digit industry, minimum 4 plants, 20% sampling fraction

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