Are We Undercounting Reallocation's Contribution to Growth?

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Abstract

There has been a strong surge in aggregate productivity growth in India since 1990, following significant economic reforms. Three recent studies have used two distinct methodologies to decompose the sources of growth, and all conclude that it has been driven by within-plant increases in technical efficiency and not between-plant reallocation of inputs. Given the nature of the reforms, where many barriers to input reallocation were removed, this finding has surprised researchers and been dubbed "India's Mysterious Manufacturing Miracle." In this paper, we show that the methodologies used may artificially understate the extent of reallocation. One approach, using growth in value added, counts all reallocation growth arising from the movement of intermediate inputs as technical efficiency growth. The second approach, using the Olley-Pakes decomposition, uses estimates of plant-level total factor productivity (TFP) as a proxy for the marginal product of inputs. However, in equilibrium, TFP and the marginal product of inputs are unrelated. Using microdata on manufacturing from five countries – India, the U.S., Chile, Colombia, and Slovenia – we show that both approaches significantly understate the true role of reallocation in economic growth. In particular, reallocation of materials is responsible for over half of aggregate Indian manufacturing productivity growth since 2000, substantially larger than either the contribution of primary inputs or the change in the covariance of productivity and size.

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1 Introduction

Reallocating inputs to higher marginal product activities will increase aggregate productivity. In recent decades, India has introduced many reforms aimed at encouraging this process, including industrial de-licensing, tariff reductions, FDI liberalization, directed lending, and lifting of small-scale industry reservations. Following these reforms in the early 1990s, India has experienced a robust increase in annual aggregate productivity growth to almost 5%. However, three recent studies looking to quantify the contribution of reallocation to this growth all find that it played very little role, and that growth was instead driven by within-plant gains in technical efficiency (Sivadasan 2009, Harrison, Martin, and Nataraj 2011, and Bollard, Klenow, and Sharma 2013).[1] BKS note that "many economists believe Indian reforms during this era improved resource allocation, [so] the absence of a growth pickup from reallocation is surprising," and call it "India's Mysterious Manufacturing Miracle." Two distinct approaches were taken by these researchers in their estimates of aggregate productivity growth (APG) due to reallocation. In this paper, we argue that both approaches artificially understate the effects of reallocation, and that a different methodology, from Petrin and Levinsohn (2012), correctly calculates the growth arising from reallocation of inputs to firms with different marginal products.

The approach in BKS uses estimates of value added (VA) production function parameters to estimate marginal products for capital and labor at every plant. If any primary input is reallocated, its contribution to aggregate reallocation is the difference in its value of marginal product between its new and old plant. But for the use of the value added production function instead of gross output (GO), this is similar to the definitions of reallocation from Basu and Fernald (2002) and Petrin and Levinsohn (2012). However, as Basu and Fernald (1997) argue, using value-added production functions will misclassify growth coming from the reallocation intermediate inputs as technical efficiency growth.

The approach in HMN and Sivadasan is to estimate gross output (GO) production functions to recover plant-level TFP residuals. They then follow Olley and Pakes (1996) to estimate contribution of aggregate reallocation to growth as the sum (across all plants) of the plant-level change in output share times the estimated plant-level average product.[2] However, in equilibrium, plant TFP may not be positively correlated with the marginal product of inputs. For instance, in an equilibrium where firms face common input prices, the marginal products for each input will be equal across firms, regardless of differences in plant-level productivity. We use a simplified version of the Hsieh and Klenow (2009) setup to illustrate that the correlation may be *negative*, in which case the Olley-Pakes decomposition will generate the wrong sign for the productivity effects of reallocation.[3]

When we apply the Olley-Pakes (OP) measurement to Indian manufacturing data, the OP

[1] We reference these papers repeatedly, and for notational convenience respectively refer to them as Sividasan, HMN, and BKS.

[2] More precisely, Olley-Pakes uses the average product relative to the unweighted industry average.

[3] Our results caution against using any APG index that focus exclusively on TFP residuals and ignore marginal products of inputs, including the widely used indices of Baily, Hulten, and Campbell (1992), Griliches and Regev (1995), and Foster, Haltiwanger, and Krizan (2001). According to Hulten, the Bailey-Hulten-Campbell (BHC) decomposition was not intended to map micro-level changes to their impact on aggregate output (indeed Hulten (1978) is the important reference on mapping micro-level technical efficiency changes to changes in aggregate output). Nishida, Petrin, and Polanec (2014) explore these types of decompositions in the context of aggregate labor productivity.

measure understates reallocation's contribution by an average of almost 7% per year (In fact, using the OP methodology, aggregate productivity has declined in India over the first decade of the 21st century). While the OP and L-P methodogies find broadly similar aggregate productivty numbers in the U.S. census data, but not in the other three countries we have data for. Using the OP decomposition on census data from Chile, Colombia, and Slovenia finds that reallocation's contribution to growth was negative and close to zero (-0.19%, -0.06%, and 0.29% per year, respectively), but using the marginal product definition the reallocation gains were much higher (respectively 4.13%, 4.09%, and 2.04% per year)

In the next section, we describe formally how the issues we discuss can arise using value added or TFP residuals. We then describe the data used in the paper for each of the five countries, and our results in those settings.

2 Calculating Productivity Growth

In this section, we first develop three strategies for calculating growth in productivity due to reallocation, in line with BKS (Value-Added), Sividasan and HMN (Olley-Pakes), and our preferred strategy, following Petrin and Levinsohn 2012 (P-L). We then show in different model economies - one with intermediate inputs, the other with distortions in relative prices - that only the P-L approach consistently correctly estimates reallocation growth.

2.1 Gross-Output vs. Value-Added Production Functions

We now show how value-added production functions count all reallocation from intermediate inputs as technical efficiency growth. Consider a continuous-time single-good economy with a representative agent that allocates output either to (intermediate) input use in production or to consumption. Let Q denote gross output, $C = Q - M$ denote the amount of output left for consumption after M units of it are used in production, and let utility be given as $U(C) = C$. The production function is given as

$$Q = f(M, \omega)$$

with ω denoting technical efficiency, $\frac{\partial f}{\partial M} > 0$, and $\frac{\partial^2 f}{\partial M^2} < 0$. The opportunity cost of using another unit of M in production is a unit of consumption so the optimal M satisfies $\frac{\partial f(M,\omega)}{\partial M} = 1$, that is, the M where the (value of the) marginal product is equated with the cost of the input.

At any instant the additional output going to consumption is given by $dC = dQ - dM$. Totally differentiating the production function and plugging in then gives

$$dC = \frac{\partial f}{\partial M} dM + \frac{\partial f}{\partial \omega} d\omega - dM = \frac{\partial f}{\partial \omega} d\omega + (\frac{\partial f}{\partial M} - 1) dM. \tag{1}$$

When M is optimal growth in consumption arises only when technical efficiency increases; there are no gains from reallocating output between consumption and production. However, if the level of M were such that $\frac{\partial f(M,\omega)}{\partial M} > 1$, then utility can be increased by reallocating output from consumption to production. True instantaneous growth from reallocation of $dM(= -dC) > 0$ is given by $(\frac{\partial f}{\partial M} - 1)dM$. If we used a value-added production function to estimate the growth from technical efficiency we get $dV(= dC) = dQ - dM$, and technical efficiency when this reallocation takes place will be overstated by$(\frac{\partial f}{\partial M} - 1)dM$.

2.2 Marginal Products of Inputs vs. TFP residuals and Olley-Pakes Reallocation

Reallocation growth measurement based on TFP residuals can be misleading, because TFP residuals and marginal products of inputs are not generally equal. If distortions & productivity are uncorrelated, the TFP of a plant is uninformative about the effect that subsidy would have on aggregate TFP (Restuccia and Rogerson 2008).

To illustrate this point, we use a simplified form of the Hsieh-Klenow setup. Consider a single-good economy with two plants that convert labor and capital into output via the production functions

$$Q_i = \omega_i \, l_i^{\beta_l} k_i^{\beta_k}, \;\; i = 1, 2$$

with ω_i denoting plant-level technical efficiency, $\omega_1 > \omega_2$, and $\beta_l + \beta_k < 1$. At the output-maximizing allocation of labor $(l_1^*, k_1^*, l_2^*, k_2^*)$ marginal products of inputs are equated across plants for each input x

$$\frac{\partial Q_1(l_1^*, k_2^*)}{\partial x} = \frac{\partial Q_2(l_2^*, k_2^*)}{\partial x} \quad x = l, k,$$

with the more productive plant 1 using more inputs in equilibrium than plant 2.

Now suppose that wedges similar to those in Hsieh and Klenow (2009) exist, where the wedges - whatever economic distortion may be causing them - can be represented by the more productive plant 1's output being subsidized at rate τ_1 and plant 2's output being taxed at rate τ_2. Wages and rental rates are assumed to be fixed. Plant 1 will use too many inputs and plant 2 will use too few. Let $(l_i^* + \Delta l_i(\tau_i), k_i^* + \Delta k_i(\tau_i))$ represent the distorted input levels of labor and capital at plant i. If these economic distortions are removed then the resulting change in plant i's output is given by integrating over the marginal products of inputs

$$\Delta Q_i = \int_{l_i^* + \Delta l_i(\tau_i)}^{l_i^*} \int_{k_i^* + \Delta k_i(\tau_i)}^{k*_i} \frac{\partial Q_i^2(l, k)}{\partial l \partial k} \, dk \, dl.$$

Aggregate output increases by $\Delta Q_1 + \Delta Q_2$, which is the difference between the gained output from plant 2 and the lost output from plant 1.

The Olley-Pakes index of aggregate productivity growth uses a definition of productivity growth that is not directly based on changes in industry value added. Instead it is based on looking at the change in output share-weighted TFP residuals in the industry:

$$\sum_i s_{it}\omega_{it} - \sum_i s_{it-1}\omega_{it-1} \tag{2}$$

where in practice ω_{it} is the estimated TFP residual (technical efficiency) at plant i at time t . This leads to the OP decomposition of $\sum_i s_{it}\omega_{it} - \sum_i s_{it-1}\omega_{it-1}$ which is given as

$$\Delta\bar{\omega}_t + [\sum (s_{it} - \bar{s}_t)(\omega_{it} - \bar{\omega}_t) - \sum (s_{it-1} - \bar{s}_{t-1})(\omega_{it-1} - \bar{\omega}_{t-1})]. \tag{3}$$

The first term is the change in the *unweighted* averages of technical efficiency at time t minus the change in *unweighted* averages of technical efficiency at time t-1 and is referred to as the "real productivity" or "technical efficiency" term. The term in brackets is interpreted as the reallocation term and measures whether the covariance between TFP residuals and output shares is increasing over time.

What does Olley-Pakes report as aggregate productivity growth from reallocation in this Hsieh-Klenow example? If we let Δs_i denote the change in output share and $\bar{\omega} = \frac{\omega_1+\omega_2}{2}$ then Olley-Pakes reallocation is defined as

$$\Delta s_1(\omega_1 - \bar{\omega}) + \Delta s_2(\omega_2 - \bar{\omega}) < 0,$$

so despite output increasing due to the removal of the wedges, Olley-Pakes-measured reallocation decreases because $\Delta s_1 < 0, (\omega_1 - \bar{\omega}) > 0, \Delta s_2 > 0$, and $(\omega_2 - \bar{\omega}) < 0$. The reason is that TFP residuals and marginal products of inputs are negatively correlated. Overall Olley-Pakes aggregate productivity growth decreases because OP technical efficiency change is equal to zero: $\bar{\omega} - \bar{\omega} = 0$, and the sum of OP technical efficiency and OP reallocation equals OP total aggregate productivity growth.[4]

3 Aggregate Productivity Growth and Reallocation

We start by illustrating the Petrin and Levinsohn (2012) decomposition of aggregate productivity growth (APG) in a setting with no intermediate inputs or capital. In Section 2.2 we generalize the setup. In both cases, APG is constructed such that, holding capital and labor use constant, aggregation of plant-level changes in technical efficiency and input reallocation add up to changes in final demand .

3.1 One-input Economy

There are N plants in the economy each producing a single good with a single input, labor l. Production technologies are given by

$$Q_i(l_i, \omega_i),$$

with ω_i denoting the level of plant i's technical efficiency. With no intermediate inputs total output at plant i that goes to final demand is just Q_i. Assuming a common wage W and letting P_i denote the price of plant i's output, APG is the difference between the change in aggregate final demand and the change in aggregate costs:

$$APG \equiv \sum_i P_i dQ_i - \sum_i W dl_i, \tag{4}$$

By totally differentiating $Q_i(l_i, \omega_i)$ one can see that (4) decomposes to:

$$\sum_i P_i \frac{\partial Q_i}{\partial \omega_i} d\omega_i + \sum_i (P_i \frac{\partial Q_i}{\partial l} - W) dl_i. \tag{5}$$

[4] Note that the average share both before and after the wedges are removed is equal to 1/2 and technical efficiencies do not change, so those terms just difference out.

The first term, the sum of each firm's productivity growth times the value of extra output each firm could produce given a marginal improvement in its productivity,represents the total gains from technical efficiency changes. The second term, the change in labor use by each firm times the difference in the marginal revenue and marginal cost of production, represents reallocation growth.In the case where a small amount of labor reallocates from j to i, so $dl_i = -dl_j$, aggregate output would change by the difference in the value of marginal products of inputs between i and j:

$$P_i \frac{\partial Q_i}{\partial l} - P_j \frac{\partial Q_j}{\partial l}.$$

In the case that labor reallocates across plants but total labor is held constant ($\sum_i dl_i = 0$), the change in aggregate output from reallocation is given by

$$\sum_i P_i \frac{\partial Q_i}{\partial l} dl_i.$$

3.2 General Setup

We now extend the model in the previous section to include multiple primary inputs (such as different types of labor and capital) as well as intermediate inputs. The production technology is now given by $Q_i(X_i, M_i, \omega_i)$, where $X_i = (X_{i1}, \ldots, X_{iK})$ is the vector of K primary input amounts used at plant i and $M_i = (M_{i1}, \ldots, M_{iJ})$ is the vector representing, for plant i, the amount of each plant j's output used as an intermediate input.[5] The total amount of output from plant i that goes to final demand Y_i is

$$Y_i = Q_i - \sum_j M_{ji},$$

where $\sum_j M_{ji}$ is the total amount of i's output that serves as intermediate input within plant i and across other plants $j \neq i$. The change of i's output that goes to final demand is therefore $dY_i = dQ_i - \sum_j dM_{ij}$. APG is again defined as the difference between the change in aggregate final demand and the change in aggregate costs, and in this generalized setup is equal to:

$$APG \equiv \sum_i P_i dY_i - \sum_i \sum_k W_{ik} dX_{ik}, \tag{6}$$

where W_{ik} equals the unit cost to i of the k^{th} primary input and dX_{ik} is the change in the use of that primary input at plant i.[6]

[5] Here we suppress their fixed cost term for transparency.

[6] In the general setup from Petrin and Levinsohn (2012), the path of primary and intermediate inputs and productivity shocks for plant i is given as $Z_{it} = (X_{it}, M_{it}, \omega_{it})$, $t \in [0, 1]$. For the entire economy they write $Z_t = (Z_{1t}, Z_{2t}, \ldots, Z_{Nt})$. Given Z_t, output quantities are determined by the production technologies and $Q_t = (Q_{1t}(Z_{1t}), \ldots, Q_{Nt}(Z_{Nt}))$. Prices are assumed to be uniquely determined by Q_t, given as $P_t = (P_{1t}(Q_t), \ldots, P_{Nt}(Q_t))$, and similarly for primary input costs $W_t = (W_{1t}(Z_t), \ldots, W_{Kt}(Z_t)))$. Y_{it} can then be directly calculated for all i and $t \in [0, 1]$.

Equation (6) decomposes as:

$$\sum_i \sum_k (P_i \frac{\partial Q_i}{\partial X_k} - W_{ik}) dX_{ik} + \sum_i \sum_j (P_i \frac{\partial Q_i}{\partial M_j} - P_j) dM_{ij} + \sum_i P_i \frac{\partial Q_i}{\partial \omega_i} d\omega_i, \tag{7}$$

where $\frac{\partial Q_i}{\partial X_k}$ and $\frac{\partial Q_i}{\partial M_j}$ are the partial derivatives of the output production function with respect to the kth primary input and the jth intermediate input respectively, dM_{ij} is the change in intermediate input j at plant i. $\sum_i P_i \frac{\partial Q_i}{\partial \omega_i} d\omega_i$ is again the gain from technical efficiency changes and reallocation is now given as

$$\sum_i \sum_k (P_i \frac{\partial Q_i}{\partial X_k} - W_{ik}) dX_{ik} + \sum_i \sum_j (P_i \frac{\partial Q_i}{\partial M_j} - P_j) dM_{ij}.$$

where the reallocation terms include a value of marginal product term and an input cost term for each plant and every primary and intermediate input.[7] We now turn to estimation.

3.3 Estimation

In the data, APG can be expressed as the weighted sum of establishment-level growth rates in value added minus the establishment-level growth rates in primary inputs and is given as

$$APG = \sum_i D_i^v dlnVA_i - \sum_i \sum_k s_{ik}^v dlnX_{ik}, \tag{8}$$

with $D_i^v = \frac{VA_i}{\sum_i VA_i}$(the value-added Domar weight) and the cost share for the kth primary input given as $s_{ik}^v = \frac{W_{ik} X_{ik}}{\sum_i VA_i}$. For estimation, we work with both gross output and value added production functions. We write the gross output production function as

$$ln(GO_i) = \sum_k \varepsilon_{ik} lnX_{ik} + \sum_j \varepsilon_{ij} dlnM_{ij} + ln\omega_i, \tag{9}$$

with ε_{ik} and ε_{ij} denoting the elasticities of gross output with respect to primary and intermediate inputs, respectively. Establishment-level gross output technical efficiency is given as $ln\omega_i$. APG can then be decomposed as

$$\underbrace{\sum_i D_i \sum_k (\varepsilon_{ik} - s_{ik}) dlnX_{ik}}_{\text{Reallocation of Labor and Capital}} + \underbrace{\sum_i D_i \sum_j (\varepsilon_{ij} - s_{ij}) dlnM_{ij}}_{\text{Reallocation of Intermediates}} + \underbrace{\sum_i D_i dln\omega_i}_{\text{Technical Efficiency}} . \tag{10}$$

where $D_i = \frac{P_i Q_i}{\sum_i VA_i}$ are gross output Domar weights and $s_{ik} = \frac{P_{ik} X_{ik}}{P_i Q_i}$ and $s_{ij} = \frac{P_{ij} M_{ij}}{P_i Q_i}$ are output shares for primary and intermediate inputs. Aggregate growth arising from the reallocation of primary inputs and intermediates inputs are given by $\sum_i D_i \sum_k (\varepsilon_{ik} - s_{ik}) dlnX_{ik}$ and $\sum_i D_i \sum_k (\varepsilon_{ij} - s_{ij}) dlnM_{ij}$, respectively. Growth from aggregate technical efficiency is given by $\sum_i D_i dln\omega_i$. We

[7] If there are widespread increasing returns to scale (IRTS), the analysis here would call that reallocation. Based on our data from the U.S., Chile, Colombia, and Slovenia, we observe constant returns to scale or decreasing returns to scale in most cases, and for more than half of those industries we reject the null hypothesis that an industry exhibits IRTS.

write the valued added production functions as

$$ln(VA_i) = \sum_k \varepsilon_{ik}^v lnX_{ik} + ln\omega_i^v, \tag{11}$$

with ε_{ik}^v denoting the elasticity of (value-added) output with respect to the primary inputs, and the establishment-level value-added technical efficiency given as $ln\omega_i^v$. In this case, APG can then be decomposed as

$$\underbrace{\sum_i D_i^v \sum_k (\varepsilon_{ik}^v - s_{ik}) dlnX_{ik}}_{\text{Reallocation of Labor and Capital}} + \underbrace{\sum_i D_i^v dln\omega_i^v}_{\text{Technical Efficiency}} \quad . \tag{12}$$

Aggregate growth arising from the reallocation of primary inputs is given by $\sum_i D_i^v \sum_k (\varepsilon_{ik}^v - s_{ik}) dlnX_{ik}$ and growth from aggregate technical efficiency is given by $\sum_i D_i^v dln\omega_i^v$. In equation (12), any growth from reallocation of intermediates will be incorrectly measured as growth from aggregate technical efficiency.

Equation (8) can be estimated directly from discrete-time data using Tornquist-Divisia approximations.[8] We estimate production function parameters for each SIC 4-digit industry for U.S. manufacturing, for each SIC 3-digit industry for Chile and Colombia, and NACE 2-digit industry code for Slovenia. In all cases, we use the proxy method from Wooldridge (2009) that modifies Levinsohn and Petrin (2003) to address the simultaneous determination of inputs and productivity.[9] We estimate production function parameters in equation (9) separately for each 3-digit industry for the Indian data using cost shares, as in BKS (2013) In the gross output case, the estimate of plant-level technical efficiency is

$$\widehat{ln\omega}_{it} = ln(GO_{it}) - \left(\widehat{\epsilon}_{jP}\, lnL_{it}^P + \widehat{\epsilon}_{jNP}\, lnL_{it}^{NP} + \widehat{\epsilon}_{jK}\, lnK_{it} + \widehat{\epsilon}_{jE}\, lnE_{it} + \widehat{\epsilon}_{jM}\, lnM_{it}\right),$$

where $\widehat{\epsilon}_{j\cdot}$ denote the estimated elasticities of gross output with respect to the inputs in industry j. We use Tornquist-Divisia approximations for each term in equation (10).[10] As regressors, we use three primary inputs and two intermediate inputs: production (blue-collar) workers L_{it}^P, non-production (white-collar) workers L_{it}^{NP}, capital K_{it} , energy E_{it} , and materials M_{it} .

In the value added case, the estimate of establishment-level technical efficiency is

$$\widehat{ln\omega^v}_{it} = ln(VA_{it}) - \left(\widehat{\epsilon^v}_{jP}\, lnL_{it}^P + \widehat{\epsilon^v}_{jNP}\, lnL_{it}^{NP} + \widehat{\epsilon^v}_{jK}\, lnK_{it}\right),$$

where $\widehat{\epsilon^v}_{j\cdot}$ denote the estimated elasticities of value added with respect to the inputs in industry j.

[8] We chain-weight to update prices on an annual basis (they are included in the Domar weights). For example, $APG = \sum_i \overline{D}_{it}^v \Delta lnVA_{it} - \sum_i \overline{D^v}_{it} \sum_k \overline{s}_{ikt}^v \Delta lnX_{ikt}$ where $\overline{D}_{it}^v$ is the average of establishment i's value-added share weights from period $t-1$ to period t, Δ is the first difference operator from period $t-1$ to period t, $\overline{s}_{ikt}$ is the average across the two periods of establishment i's expenditures for the kth primary input as a share of establishment-level value-added.

[9] The approach is robust to the comment by Ackerberg, Caves, and Frazer (2015) and is one line of code in Stata.

[10] For the reallocation terms we use the approximations $\sum_i \overline{D}_{it} \sum_k (\varepsilon_{ik} - \overline{s}_{ikt}) \Delta lnX_{ikt}$ and $\sum_i \overline{D}_{it} \sum_j (\varepsilon_{ij} - \overline{s}_{ijt}) \Delta lnM_{ijt}$. For the technical efficiency term we use $\sum_i \overline{D}_{it} \Delta ln\omega_{it}$.

4 Data

This section describes our plant-level manufacturing data from India, the U.S., Chile, and Colombia, and firm-level data from Slovenia.

Indian Manufacturing Data For India, we use plant-level data from the Annual Survey of Industries (ASI) from 1999-2010, which are an annual survey of Indian manufacturing plants conducted by the Indian Ministry of Statistics. The ASI sampling frame includes all registered factories (who are collectively responsible for around 80% of total manufacturing output in India) employing 10 or more workers using power or 20 or more workers without using power, and surveys about 50,000 plants in each year, and designed to be representative at the state by 4-digit industry level. Plants above a time-varying employment threshold (100 to 200 workers) are surveyed every year (as are plants who are rare in their state/industry block). The remaining plants are sampled randomly.[11][12] Plant-level variables collected in the ASI include: (1) values of output, materials, and fuels, (2) the book value of fixed assets, which we treat as capital, (3) employment and wages for blue workers and all other employees, and (4) industry codes and (in 1998 and later) plant-level longitudinal identifiers. All values are deflated following Alcott et. al. (2015)

The ASI is the same survey data that BKS (2013) use — we use 1999-2010, whereas BKS used 1980-2007. Sivadasan (2009) and HMN (2011) use the ASI for subsets of BKS's sample period. To facilitate comparison with BKS (2013), we use three samples that BKS employ. The first sample is "All ASI," in which we have all plant-year observations in the ASI for which we can measure an annual growth rate–i.e., plants that appear in any two consecutive years in our sample period: about 19,000 to 38,000 plants in each year. The second sample is the "census" sample: the firms who are supposed to be surveyed each year. The third sample is the "Large Plants" sample, for plants with more than 200 employees — these plants are surveyed every year (and, since BKS did not have access to longitudinal identifiers, are the ones who are easiest to match over time given firm characteristics), and contains about 4,000 to 8,000 plants in each year. To give a sense of the difficulty of tracking smaller plants without the identifiers, our "All ASI"'s employment totals are 1.5 to 3.3 million larger than the employment totals for BKS's "All ASI" samples in each year that our samples overlap, but for our "Large Plants" sample the employment totals are within 2% of BKS's employment for every year.

U.S. Manufacturing Data For the United States,we use plant-level data from the Census Bureau's Annual Surveys of Manufactures, from 1976-1996. To construct our variables, we follow the detailed description in the data appendix of Petrin, White and Reiter (2011). Here we provide a brief description of the variables. For labor, we observe production worker hours and production worker wages, the average number of production workers, total employment, and total salaries and

[11] Firms are guaranteed to be surveyed on a rotating basis - for instance every 3 years - where the gap between years is decreasing in firm size. Depending on the budget each year, additional firms are randomly sampled. The sampling weights are provided.

[12] Due to the nature of the sampling, if we included all plants in our estimation a substantial portion of aggregate productivity growth would be misclassified as being due to "entry." To avoid this issue, for each year, we only include plants who were surveyed in the previous year.

wages. For capital, we observe book values of assets and capital expenditures. We use industry deflators and depreciation rates from the BEA and the perpetual inventory method to construct capital stocks from these measures. Our measure of nominal gross output is the total value of shipments. For intermediate inputs, we use measures of energy and materials. For energy, we use the sum of the cost of fuels and purchased electricity. For materials inputs, we use the total cost of materials minus energy costs. Value added is gross output minus materials and energy. We use industry-level deflators from the NBER-CES Productivity Database to convert from nominal to real values.

Chilean and Colombian Manufacturing Data The Chilean and Colombian data are annual and span the periods of 1979-95 and 1977-91, respectively. Here we provide a brief overview of these data. Numerous other productivity studies use them, and we refer interested readers to those papers for a more detailed data description.[13]The Chilean data, provided by Chile's Instituto Nacional de Estadistica (INE), are unbalanced panels and cover all manufacturing plants with at least 10 employees. The Colombian data from the Annual Manufacturing Survey, provided by Colombia's Departamento Administrativo Nacional de Estadistica (DANE), are also unbalanced panels and cover all plants for the years 1977-82 and the plants with at least 10 employees for the years 1983-91. In both data sets, plants are observed annually and they include a measure of nominal gross output, two types of labor, capital, and intermediate inputs, including fuels and electricity. Labor is the number of person-years hired for production, and plants distinguish between their blue- and white-collar workers. Liu (1991) documents the method for constructing the real value of capital for the Chilean data, and we use the same method for the Colombian data.[14] We use double-deflated value added for Chilean results and single-deflated value added for Colombia because intermediate input deflators are not available there.

Slovenian Manufacturing Data For Slovenian data, we use the annual accounting data provided by the Slovenian Statistical Office and other sources from 1994 through 2004. Our data are an unbalanced panel and cover all manufacturing firms.We use single-deflated value added because no intermediate input deflator is available. The Slovenian data are distinct from other data we use in that it is firm-level data and not plant-level data and there exists both a firm-level deflator and a capacity utilization rate for a subset of firms.

As an ex-socialist country, Slovenia went through extensive changes in its economic system starting in 1988. The deregulation of entry in 1988 allowed the setup of privately owned firms and resulted in expansion of private businesses. In addition, price and wage liberalization took place during the period of 1987-93. The process of privatization of state-owned firms started in 1994 and

[13]See Liu (1991), Liu (1993), and Levinsohn and Petrin (2003) for the Chilean data and Roberts (1996) for the Colombian data.

[14]For the Chilean data, the real value of capital is a weighted average of the peso value of depreciated buildings, machinery, and vehicles. We assume each has a depreciation rate of 5%, 10%, and 20%, respectively. Some plants don't report initial capital stock, although they record investment. When possible, we used a capital series that they report for a subsequent base year. For a small number of plants, they don't report capital stock in any year. We estimated a projected initial capital stock based on other reported plant observables for these plants. We then used the investment data to fill out the capital stock data.

continued throughout the 1990s. For this reason, several empirical studies of productivity dynamics have used Slovenian data.[15]

5 Results

Columns 1-5 of Table 1 present the annual growth rates of value-added, primary inputs costs (production worker labor, non-production worker labor, and capital), and aggregate productivity growth for the Indian data. Aggregate productivity growth is defined as column 1 less the sum of columns 2-4. Value added growth in India averaged 7% per annum, although the total amount spent on primary inputs increased by 1.16%. Figure 1 shows a graph of the annual growth rates of aggregate value-added and aggregate productivity (equation 6) for all Indian manufacturing plants (All ASI) from 2000-2010. The difference between the two is the sum of the growth rates of primary input costs. As the graph shows, P-L aggregate productivity growth is highly correlated ($\rho = .96$)with the growth of value added as most of the fluctuations in aggregate productivity are primarily associated with fluctuations in value-added.

Table 2 presents the decomposition of APG by technical efficiency and reallocation measures. Reallocation of intermediates makes a large contribution, accounting for 2.92% – over 85% of the total amount of reallocation, and over 50% of overall productivity growth. Calculating technical efficiency growth without taking into consideration gaps between intermediates' revenue shares and elasticities overstates its true contribution by a factor of two.

Table 3 compares the P-L decomposition to the commonly used Olley-Pakes measure. Only the P-L approach adds up to the total productivity gains. The Olley-Pakes decomposition shows that, nevertheless, the productivity of the average plant in India decreased over the time period, and the covariance of size and productivity increased by an average of only .16%. The correlation of annual estimated OP and P-L productivity gains is $-.06$.

In Table A4, we show the equivalent annual averages for Table 3 using not only cost-shares to measure production function elasticities, but also OLS and Wooldridge's (2009) modification of Levinsohn and Petrin (2003), using both energy and materials and proxies. The results for P-L are fairly consistent across strategies - using W-LP suggests more reallocation than do cost shares, while the OP results are sensitive to the choice of estimator. In Table A5, we show that our decompositions are reasonably similar if instead of using all Indian plants, we use either of the two samples in BKS: firms with over 200 employees, and firms who *de jure* were meant to be surveyed each year (the "census" sample).

Figure 2 decomposes P-L aggregate productivity growth. In most years, reallocation contributes the most, and reallocation of intermediates is more important than that of primary inputs.

Table A1 summarizes aggregate value added and primary input growth for the U.S., Chile, Colombia, and Slovenia. Using the APG measure, most of the countries' manufacturing sectors experienced significant productivity growth over the respective sample periods: 1.90%, 2.88%, 3.10%, and 3.88% per year in the U.S., Chile, Colombia, and Slovenia, respectively.

Table A2 summarizes the APG decomposition for the U.S., Chile, Colombia, and Slovenia.

[15]See, for example, de Loecker and Kornings (2006) and Bartelsman, Haltiwanger, and Scarpetta (2010).

With the exception of the latter country, as in the Indian manufacturing sector reallocation of materials plays a large role in measured aggregate productivty growth – respectively .47%, 2.77%, 1.17%, and -.37%.

Table A3 compares the APG and OP decomposition measures. The OP measures of total produtivity growth – 1.26% per year for the U.S., −0.23% per year for Chile, 0.09% for Colombia, and 0.37% for Slovenia – are lower than their APG counterparts everywhere, in particular the latter three countries. The OP measures overstates total reallocation in the US by .35%, but understates it by 4.32%, 4.15% and 1.75% in Chile, Colombia, and Slovenia, respectively.

6 Conclusions

Recent studies have found that reallocation of resources across plants played surprisingly little role in the large increase in aggregate productivity in India in recent years. We argue that these findings may be an artifact of the way these studies measure the contributions of technical efficiency growth and reallocation. Using data from five countries — India, the U.S., Chile, Colombia, and Slovenia — we show that ignoring reallocation of intermediate inputs significantly understates the contribution of reallocation in aggregate productivity growth, and correspondingly overstates the role of within-plant technical-efficiency growth. In these five countries using TFP residuals instead of marginal products of inputs underestimates the contribution of reallocation. Our findings have broader implications for the class of reallocation estimators including Baily, Hulten, and Campbell (1992), Griliches and Regev (1995), Olley and Pakes (1995), and Foster, Haltiwanger, and Krizan (2001) and all of their derivatives. We find that reallocation made a large contribution to aggregate productivity growth in the Indian manufacturing sector in recent years, thus resolving the mystery of India's manufacturing growth. The findings in BKS, therefore may be reversed, with reallocation accounting for over half of APG versus the under 10% contributed by primary inputs.

Table 1: Percentage Growth Rates of Value-Added, Primary Input Costs and Aggregate Productivity All Indian Manufacturing Plants, 2000–2010.

Year	(1) Value Added	(2) Production labor costs	(3) Non-production labor costs	(4) Capital costs	(5) P-L APG
2000	2.42	-0.46	-0.19	-0.16	3.23
2001	4.98	-0.61	-0.18	-0.09	5.86
2002	5.00	0.09	-0.06	0.52	4.45
2003	-0.21	-0.37	-0.10	-0.59	0.85
2004	13.33	0.48	0.20	0.95	11.69
2005	10.92	0.35	0.07	0.90	9.61
2006	15.63	0.64	0.30	1.76	12.93
2007	9.89	0.69	0.38	2.45	6.37
2008	1.87	0.08	0.17	1.73	-0.11
2009	2.46	0.02	-0.02	1.61	0.84
2010	10.58	0.49	0.17	1.43	8.49
mean	6.99	0.13	0.07	0.96	5.84
s.d.	5.28	0.45	0.19	0.95	4.47

Note: (1) - (2) - (3) - (4)= (5)

Table 2: Aggregate Productivity Growth Decompositions
All Indian Manufacturing Plants, 2000–2010

		Aggregate Productivity Growth Contributions from...				
	(1)	(2)	(3)	(4)	(5)	(6)
Year	P-L Aggregate Productivity Growth	P-L Technical Efficiency	P-L Technical Efficiency (Corrected)	P-L Reallocation Primary	P-L Reallocation Intermediates	P-L Reallocation Total
2000	3.23	2.71	2.69	0.52	0.02	0.55
2001	5.86	5.40	7.17	0.47	-1.78	-1.31
2002	4.45	4.21	1.76	0.24	2.45	2.69
2003	0.85	0.41	0.03	0.44	0.38	0.82
2004	11.69	11.07	2.61	0.63	8.46	9.09
2005	9.61	9.08	8.01	0.53	1.07	1.60
2006	12.93	12.35	6.94	0.58	5.41	5.99
2007	6.37	5.82	-0.82	0.55	6.64	7.19
2008	-0.11	-0.49	-3.64	0.37	3.15	3.53
2009	0.84	1.01	1.18	-0.17	-0.17	-0.33
2010	8.49	8.16	1.64	0.33	6.52	6.84
mean	5.84	5.43	2.51	0.41	2.92	3.33
s.d.	4.47	4.35	3.60	0.22	3.37	3.46

Note: Column 1 is the Petrin-Levinsohn (P-L) (2012) measure of aggregate productivity growth. Columns 2-3 are P-L technical efficiency growth, where Column 2 does not correct for a "gap" between materials' production function elasticity and revenue share. Columns 4 and 5, respectively demonstrate the contributions of the reallocation of primary and intermiate inputs to APG growth. Column 6 is the sum of columns 4 and 5, showing the total contribution of reallocation. Output elasticities are estimated by revenue shares. Each column approximates a continuous-time measure of growth using discrete-time data.

Table 3: Aggregate Productivity Growth Decompositions
Petrin-Levinsohn vs. Olley-Pakes
Average Annual Percentage Growth Rates

		Aggregate Productivity Growth Contributions from...			
	(1)	(2)	(3)	(4)	(5)
	P-L	P-L	OP		
		Technical	Technical	P-L	OP
	APG	Efficiency	Efficiency	Reallocation	Reallocation
Year		(Corrected)		Total	
2000	3.23	2.69		0.55	
2001	5.86	7.17	-2.09	-1.31	3.67
2002	4.45	1.76	-0.27	2.69	-3.37
2003	0.85	0.03	-3.17	0.82	0.02
2004	11.69	2.61	-4.62	9.09	-7.96
2005	9.61	8.01	0.83	1.60	10.86
2006	12.93	6.94	-0.33	5.99	0.28
2007	6.37	-0.82	-0.29	7.19	-5.27
2008	-0.11	-3.64	0.59	3.53	2.04
2009	0.84	1.18	-2.39	-0.33	0.93
2010	8.49	1.64	-0.23	6.84	0.37
mean	5.84	2.51	-1.20	3.33	0.16
s.d.	4.47	3.60	1.78	3.46	5.15

Note: Column 1 is Aggregate Productivity Growth. Columns 2 and 3 show the contribution of technical efficiency growth for, respectively, P-L and OP. Columns 4 and 5 show the contribution of reallocation, again respectiely for P-L and OP. Output elasticities are estimated by revenue shares. Each column approximates a continuous-time measure of growth using discrete-time data.

Table A1: Percentage Growth Rates Per Year, Value-Added, Primary Input Costs and Aggregate Productivity, The U.S., Chilean, Colombian, and Slovenian Manufacturing.

Country	(1) Value Added	(2) Production labor costs	(3) Non-production labor costs	(4) Capital costs	(5) P-L APG
U.S.	1.74	-0.25	-0.02	0.11	1.90
Chile	3.62	0.48	0.37	-0.11	2.88
Colombia	4.14	0.55	0.43	0.06	3.10
Slovenia	6.96	1.11	0.84	1.13	3.88

Note: See Table 1 for details

Table A2: Aggregate Productivity Growth Decompositions
Petrin-Levinsohn vs. Olley-Pakes, Chilean, Colombian, and Slovenian Manufacturing
Average Annual Percentage Growth Rates

		Aggregate Productivity Growth Contributions from...				
	(1)	(2)	(3)	(4)	(5)	(6)
Country	P-L Aggregate Productivity Growth	P-L Technical Efficiency	P-L Technical Efficiency (Corrected)	P-L Reallocation Primary	P-L Reallocation Intermediates	P-L Reallocation Total
U.S.	1.90	1.40	0.76	0.50	0.47	0.97
Chile	2.88	1.01	-2.01	1.36	2.77	4.13
Colombia	3.10	0.82	-0.11	2.92	1.17	4.09
Slovenia	3.88	1.44	1.77	2.41	-0.37	2.04

Note: See Table 2 for details

Table 3: Aggregate Productivity Growth Decompositions
Petrin-Levinsohn vs. Olley-Pakes
Average Annual Percentage Growth Rates

		Aggregate Productivity Growth Contributions from...			
	(1)	(2)	(3)	(4)	(5)
	P-L	P-L	OP		
		Technical	Technical	P-L	OP
	APG	Efficiency	Efficiency	Reallocation	Reallocation
Country		(Corrected)		Total	
U.S.	1.90	0.76	0.06	0.97	1.32
Chile	2.88	-2.01	-0.05	4.13	-0.19
Colombia	3.10	-0.11	0.16	4.09	-0.06
Slovenia	3.88	1.77	0.09	2.04	0.29

Note: See Table 3 for details

Table A4: Indian Mean Aggregate Productivity Growth Decompositions
Petrin-Levinsohn vs. Olley-Pakes
Robustness to Production Function Estimation

		Aggregate Productivity Growth Contributions from...			
	(1)	(3)	(4)	(6)	(7)
	P-L	P-L	OP		
		Technical	Technical	P-L	OP
	APG	Efficiency	Efficiency	Reallocation	Reallocation
Elasticities:		(Corrected)		Total	
Cost-Shares	5.84	2.51	-1.20	3.33	0.16
OLS	5.74	1.49	0.18	4.26	-0.62
WLP-E	6.62	1.09	-20.68	5.53	14.03
WLP-M	8.03	2.93	-3.28	5.11	-0.06

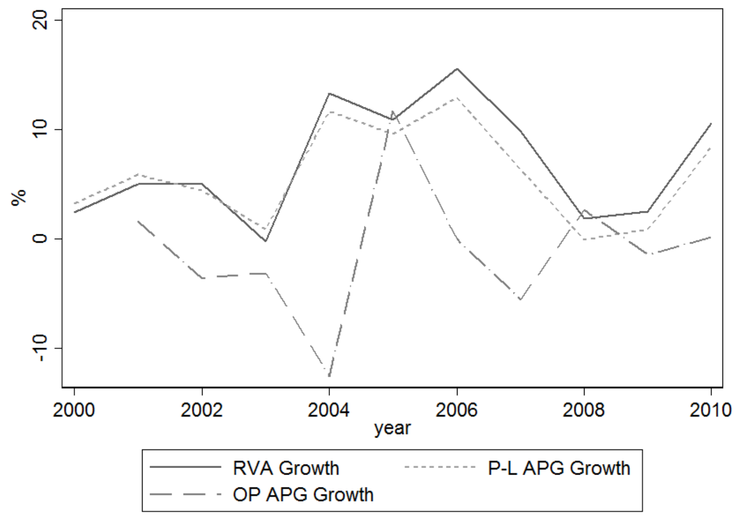
Note: Production functions are estimated using the method in the columns.

Table A5: Indian Mean Aggregate Productivity Growth Decompositions
Petrin-Levinsohn vs. Olley-Pakes
Robustness to Sample

		Aggregate Productivity Growth Contributions from...			
	(1)	(3)	(4)	(6)	(7)
	P-L	P-L	OP		
		Technical	Technical	P-L	OP
	APG	Efficiency	Efficiency	Reallocation	Reallocation
Sample		(Corrected)		Total	
All Firms	5.84	2.51	-1.20	3.33	0.16
>200 Employees	5.03	1.95	-1.75	3.08	-0.03
"Census" Sample	5.23	2.29	-1.64	2.93	-0.01

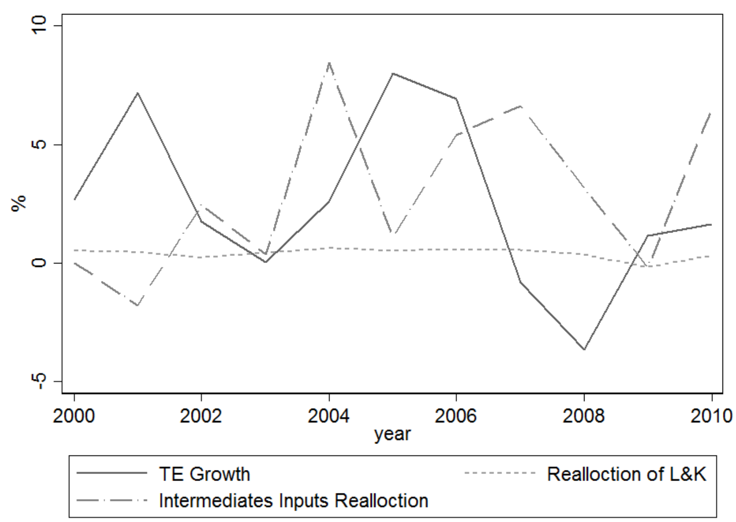
Note: Production functions are estimated using within-sample cost-shares

Figure 1: Value Added and Aggregate Productivity Growth, Indian Manufacturing



Note: This figure plots the aggregate estimated productivity growth measures from Table 3

Figure 2: Aggregate Productivity Growth from Reallocation, Decomposed by Source



Note: This figure decomposes reallocation and technical efficiency's contribution to growth

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