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India's mysterious manufacturing miracle ☆

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ABSTRACT

Using data on formal manufacturing plants in India, we report a large but imprecise speedup in productivity growth starting in the early 1990s (e.g., 1993–2007 compared to 1980–1992). We trace it to productivity growth within large plants (200 workers or more), as opposed to reallocation across such plants. As many economists believe Indian reforms during this era improved resource allocation, the absence of a growth pickup from reallocation is surprising. Moreover, when we look across industries we fail to robustly relate productivity growth to prominent reforms such as industrial de-licensing, tariff reductions, FDI liberalization, or lifting of small-scale industry reservations. Even under a generous reading of their effects, these reforms (at least as we measure them) account for less than one-third of the rapid productivity growth in Indian manufacturing from 1980–2007.

1. Introduction

Given their large populations and initial poverty, rapid economic growth in India and China in recent decades may have contributed more to world welfare than all of the growth experienced by the rest of the world's population combined (see related evidence in Pinkovskiy and Sala-i-Martin, 2009). There appears to be a growing consensus about a few aspects of China's growth speedup: growth has been particularly rapid in manufacturing (Young, 2003; and Bosworth and Collins, 2008), and has been facilitated by the displacement of inefficient state-owned enterprises with new, more efficient private enterprises (Brandt et al., 2009; and Hsieh and Klenow, 2009). In contrast, major questions about India's growth transition remain unanswered.

Did output growth pick up in India's manufacturing sector? Did reallocation of capital, labor, and materials from less-efficient to more-efficient incumbents lift the growth rate? Did pre-existing plants experience rapid productivity growth? How important was input growth versus residual productivity growth? In turn, what quantitative role did specific Indian policy reforms, such as trade liberalization and de-licensing, play in India's manufacturing growth?

We analyze data on large, formal Indian manufacturing plants from the 1980–2007 Indian Annual Survey of Industries (ASI) to decompose output growth into input growth vs. productivity growth, and into within-plant growth vs. reallocation

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across plants. We further correlate growth across industry-years to policy reforms such as de-licensing, trade and FDI liberalization, and removal of small-scale industry reservations.

We find evidence of a sizable speedup (over 5 percent per year) in aggregate productivity growth beginning around the early 1990s. The pickup arises from changes within plants over time, not reallocation from low to high productivity incumbents.

Across industry-years, we are unable to relate much of the growth to reforms such as de-licensing, trade and FDI liberalization, or lifting of small-scale industry reservations. Even taking the high end of our estimates, which are similar to previous studies, these observable reforms account for less than half of manufacturing productivity growth in India from 1980–2007, and essentially none of the speedup. Other studies find important effects, to be sure, but do not account for most of the growth (or growth pickup) we see.[1] A manufacturing miracle has occurred in India, but of mysterious origin. This echoes the qualitative conclusion of a recent book by Bardhan (2010).

Our findings (or lack thereof) must be taken with even more caution than usual. The time series is not long, and the annual growth rates are distressingly noisy. Our metrics for policy are imperfect, as is the methodology for measuring productivity growth. The effects of policy might not show up in industry productivity growth immediately following the reforms or at all. Finally, we are only analyzing large, formal manufacturing plants—to the exclusion of most workers in manufacturing and other sectors (services, agriculture).

The rest of the paper is organized as follows. In Section 2 we define our measure of productivity growth. Section 3 provides an overview of the Indian economy and details about the data. Section 4 shows the estimates of productivity growth using plant-level data. In Section 5 we provide details about the reforms that took place in India in the 1980s and 1990s, as well as evidence about the effects of these reforms on industry and aggregate productivity. Section 6 concludes.

2. Growth accounting methodology

Basu et al. (2009) show that, under certain conditions, a key contributor to welfare is the present and future behavior of aggregate total factor productivity (TFP). With this motivation, we try to estimate TFP growth rates in Indian manufacturing. We also decompose the growth into increased efficiency of individual plants vs. growth due to reallocation of resources across economic units, following Basu and Fernald (2002), Petrin and Levinsohn (2011), Petrin et al. (2011), and others.

Aggregate TFP growth is aggregate value added growth less aggregate input growth (both deflated). It can be decomposed into growth from plant efficiency, reallocation of inputs across plants within sectors, reallocation of inputs between sectors, and returns to scale. For clarity of exposition, consider the case of one good (Y with price P_Y) and one input (X with price P_X). In this special case, aggregate TFP growth in Basu and Fernald (2002) is

$$da = dy - \sum_i \frac{P_X X_i}{P_Y Y} dx_i,$$

where i refers to plant i,

$$dy = \sum_i \frac{Y_i}{Y} dy_i$$

and

$$dy_i = \frac{\Delta y_i}{y_i},$$

and similarly for dx. Some manipulation allows us to separate out average plant-level growth in technical efficiency:

$$da = \sum_i \frac{P_Y Y_i}{P_Y Y}(dy_i - dx_i) + \sum_i \left(\frac{P_Y Y_i}{P_Y Y} - \frac{P_X X_i}{P_Y Y}\right) dx_i.$$

The first term is a value added weighted average of plant efficiency growth rates. This first term should capture increasing returns to scale, technological change and improvements in labor quality. We can split the second term into growth tied to aggregate profits and growth due to reallocation, respectively:

$$da = \sum_i \frac{P_Y Y_i}{P_Y Y}(dy_i - dx_i) + \left(\frac{P_Y Y - P_X X}{P_Y Y}\right) dx + \sum_i \left(\frac{P_Y Y_i}{P_Y Y} - \frac{P_X X_i}{P_X X}\right) dx_i. \tag{1}$$

The middle term in Eq. (1) reflects that input growth is "worth" more socially than it costs privately in the presence of economic profits. As described by Basu and Fernald (2002), the economic profit rate for plant i is equal to $1 - \frac{\gamma_i}{\mu_i}$, where γ_i is the degree of returns to scale and μ_i is the markup of price over marginal cost. Thus positive economic profits reflect even bigger markups than returns to scale.

[1] Recent examples include Chamarbagwalla and Sharma (2011), Sharma (2008), Sivadasan (2009), Chari (2010) and Topalova and Khandelwal (2011).

The third term in Eq. (1) reflects reallocation of inputs to plants whose output share $\frac{Y_i}{Y}$ is larger than their input share $\frac{X_i}{X}$—and hence are more productive. Another way to express this gain from reallocation is in terms of productivity gaps. Let the value of the average product of input X for plant i be $VAP_i = \frac{P_Y Y_i}{X_i}$, and the average for the whole economy be $VAP = \frac{P_Y Y}{X}$. Then the reallocation term can be re-written as:

$$\sum_i \left(\frac{P_Y Y_i}{P_Y Y} - \frac{P_X X_i}{P_Y Y}\right) dx_i = \frac{\sum_i (VAP_i - VAP)\Delta x_i}{P_Y Y}.$$

If inputs increase for plants with higher-than-average output per unit of input, then aggregate TFP increases.

We can further split the reallocation term into reallocation of inputs across plants within a sector and reallocation of inputs between sectors. Let $VAP_j \equiv \frac{P_Y Y_j}{X_j}$ denote the value of the average product of input X in sector j. Then if we add and subtract $(\frac{P_Y Y_j}{X_j})(\frac{\Delta x_i}{P_Y Y_i})$ from the reallocation term we get the following:

$$\begin{aligned}
&\sum_i \left(\frac{P_Y Y_i}{P_Y Y} - \frac{P_X X_i}{P_Y Y}\right) dx_i \\
&\quad = \sum_j \sum_{i\in j} \left(\frac{P_Y Y_i}{X_i} - \frac{P_Y Y_j}{X_j}\right) \frac{\Delta x_i}{P_Y Y} + \sum_j \sum_{i\in j} \left(\frac{P_Y Y_j}{X_j} - \frac{P_Y Y}{X}\right) \frac{\Delta x_i}{P_Y Y} && (2)\\
&\quad = \sum_j \frac{P_Y Y_j}{P_Y Y} \sum_{i\in j} \left(\frac{P_Y Y_i}{X_i} - \frac{P_Y Y_j}{X_j}\right) \frac{\Delta x_i}{P_Y Y_j} + \sum_i \left(\frac{P_Y Y_j}{X_j} - \frac{P_Y Y}{X}\right) \frac{\Delta x_j}{P_Y Y}, && (3)
\end{aligned}$$

where $\Delta x_j = \sum_{i\in j} \Delta x_j$. The first term in Eq. (3) is reallocation of inputs across plants within a sector while the second term is reallocation of inputs across sectors.

Having described the general way in which we calculate aggregate TFP growth and its components, we now provide a few details about our implementation. First, as we will describe below, in the ASI entry and exit are conflated with unmatched continuing plants. If we aggregate "entrants" and "exiters", the resulting changes due to net entry are extremely noisy. We therefore focus only on incumbent plants in each period.

Second, to avoid double-counting of output and understatement of aggregate manufacturing TFP growth, we work with value added rather than gross output. Nominal value added of plant i is $P_i^Y Y_i = P_i^Q Q_i - P_i^M M_i - P_i^F F_i$, where Q_i is gross output, M_i are materials inputs (other than fuels), and F_i are fuel inputs.

Third, we have 2-digit gross output price deflators, which we use to deflate gross output and construct materials deflators at the 2-digit industry level. We use an economy-wide deflator for capital, and the number of employees for labor (white collar and blue collar, respectively).

Fourth, we follow Basu and Fernald (1997) in calculating Divisia real value added growth as

$$dy_i = \frac{dq_i - \beta_{st}^M dm_i - \beta_{st}^F df_i}{1 - \beta_{st}^M - \beta_{st}^F}, \tag{4}$$

where β_{st}^M is the share of materials expenditure in nominal output for the sector-year.[2]

Finally, we calculate plant efficiency growth as

$$da_i = dy_i - \sum_k \alpha_{st}^k dx_i^k, \tag{5}$$

where α_{st}^k are sector-year input cost shares, assuming a 15% rental price of capital.[3] There are three inputs: fixed assets, skilled labor and unskilled labor. We calculate all growth rates as 100 times the log difference, and all weights as Tornquist shares: $0.5 \times (w_t + w_{t-1})$. See Appendix A for more details.

3. Indian manufacturing data

3.1. Backdrop of the Indian economy

Prior to the global financial crisis, the Indian economy overall was growing at nearly double digit rates. The transition from the "Hindu" rate of 3% per annum to 9.7% in 2007 has been widely studied and publicized. Fig. 1 shows the evolution

[2] We exclude shares outside the unit interval when calculating the average. As a robustness check, we also calculated Divisia value added using total input costs (materials, fuels, capital and labor) instead of nominal output in the denominator of β_{st}^M. This has the effect of dramatically increasing the observed productivity growth speedup.

[3] We test the robustness of our productivity estimates to lower (10%) and higher (20%) rental rates of capital and find no significant differences. These results are available in an Online Appendix.

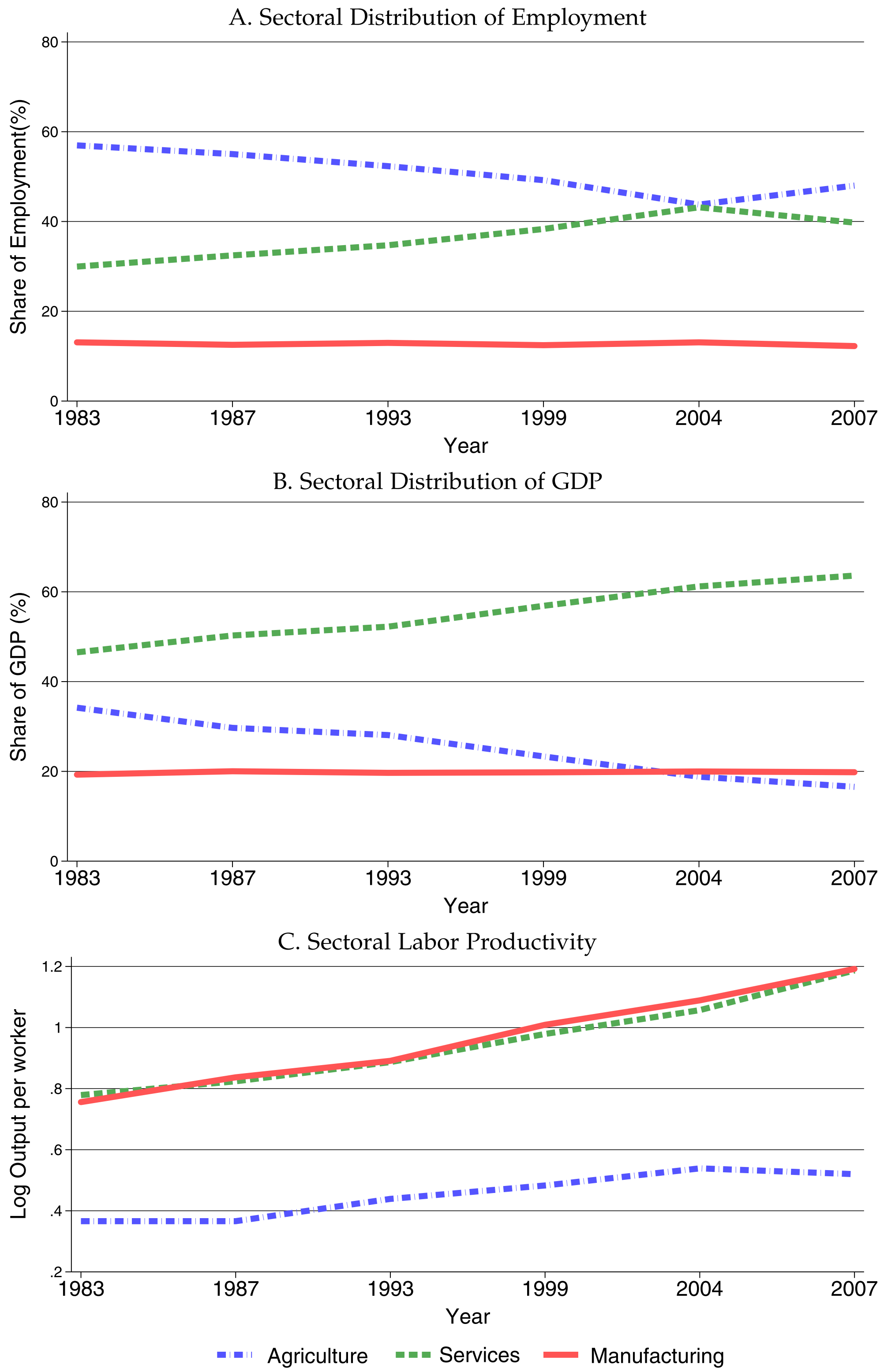

Fig. 1. Sectoral distribution and productivity in the Indian economy. Hnatskovska and Lahiri (2011) calculations from National Sample Surveys, which include both formal and informal activity in each sector.

of manufacturing, services, and agriculture amidst India's growth transition. The growth transition has been accompanied by rising fractions of employment and value added in the services sector (Panels A and B). The mirror image is the contraction of the agricultural sector. Manufacturing has maintained a surprisingly steady share of employment (∼13%) and value added (∼20%). Meanwhile, manufacturing and services have been the main drivers of labor productivity growth (Panel C). Similar trends are observed in total factor productivity growth across sectors. Thus, manufacturing has been an important driver of overall productivity growth, though services have played the dominant role.

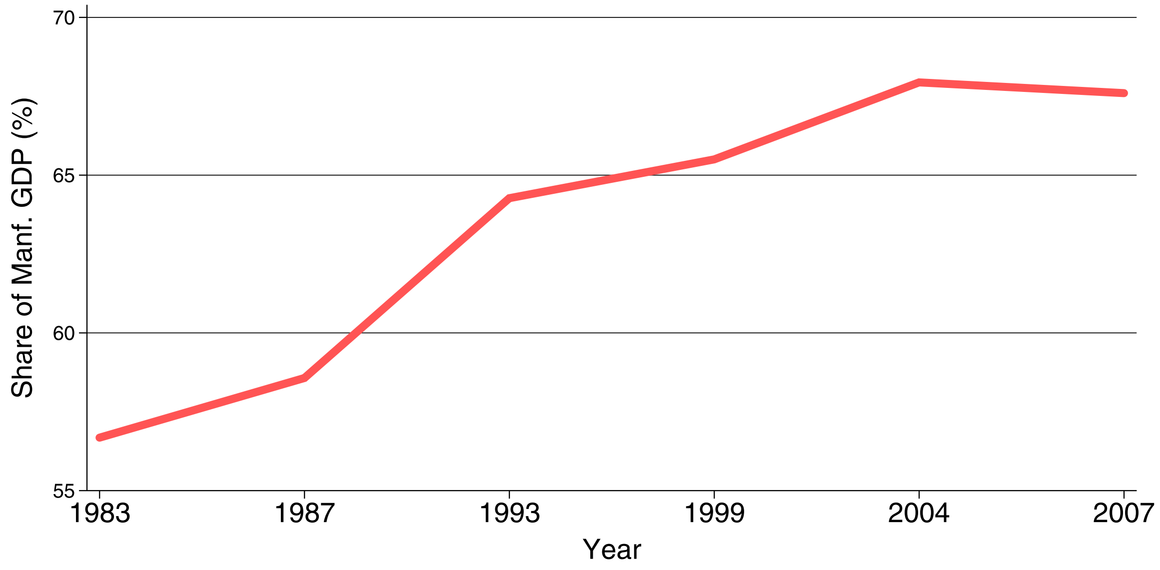

Fig. 2. Formal sector share within manufacturing sector. The graph shows the percentage of manufacturing GDP (at 1999–2000 prices) accounted for by the formal sector. The data were collected from the National Accounts Statistics of India.

All three panels of Fig. 1 are based on estimates of formal plus informal employment and value added in each sector. As our data analysis will focus on the formal manufacturing sector, it is important to get a sense of the relative size of formal manufacturing relative to informal manufacturing. Fig. 2 shows that formal manufacturing accounted for 56% of GDP generated in manufacturing in the early 1980s, and that this share has steadily risen over time. By the end our sample in 2007, formal plants account for 68% of manufacturing GDP. Though most manufacturing output is in the formal sector, most manufacturing employment appears to be in the informal sector—around 80% according to Hsieh and Klenow (2012). In contrast to the falling share of informal output, they report a slightly rising share of informal employment, from 79% in 1989 to 80.5% in 2005.

3.2. Plant-level data: annual survey of industries

The Annual Survey of Industries (ASI), which is conducted by the Indian Ministry of Statistics, is the only annual survey of Indian manufacturing plants. We use the plant-level micro data from 1980–1981 to 2007–2008 (with the exception of the 1995–1997 surveys, which are missing or inconsistent). Despite its coverage, and growing use by economic researchers, there are substantial caveats. We outline these here—for further details, see Appendix A.

The ASI sampling frame consists of all registered factories employing 10 or more workers using power, or 20 or more workers without using power. The largest plants, which we call the "Census sample", are surveyed every year. The size threshold for the Census sample varied over this period between 50 and 200 workers (see Table A.1), but all plants employing 200 or more workers are always surveyed. The remaining plants are sampled randomly, and we always weight by the inverse of the sampling probabilities.

Plants report data on the value of output, materials and fuels, although from 1996–1997 onwards up to one-third of these observations are missing. Capital is measured by the book value of fixed assets, and employment and wages are divided between blue collar workers and all other employees. We construct a common industry concordance for the NIC1970, NIC1987, NIC1998 and NIC2004 coding schemes, which gives just under 100 roughly 3-digit industries with a common definition over the entire period. We focus on plants in these industries who report these basic variables. There are substantial numbers of extreme outliers, especially since 1996–1997, and we attempt to reduce their influence by top-coding and bottom-coding the 1% tails ("Winsorizing") for all plant-level variables prior to aggregation.

Fig. 3 plots the sizes of the full ASI sample, the Census sample, and the sample of plants employing 200 or more workers over the period. Vertical lines reflect publicly announced changes in the sampling methodology. There are two gaps: the first gap reflects the missing 1995–1996 (no survey was conducted in that year); the second gap reflects the fact that the 1996–1997 survey substantially differs from the 1997–1998 survey, both in the sampling methodology and the survey form. The total value added captured in the 1996–1997 survey is more than a quarter less than that in the 1994–1995 or 1997–1998 surveys, as shown in Table A.2. Because of this, we drop the 1996–1997 survey year from the subsequent analysis; our main results are strengthened if we instead retain it. Table A.2 provides more details about the distribution of employment across plants of various sizes as well as evolution of employment and total value added (in billions of 2005 US dollars) across the three samples—all ASI plants, Census plants and plants with employment greater than 200 employees.

As explained, we are interested in decomposing productivity growth into that occurring within plants versus across plants. The publicly available ASI micro data contains no plant identifiers until 1998, but by comparing plant records in adjacent years in the Census sample, we are able to construct an imperfect panel. Our algorithm searches for unique matches

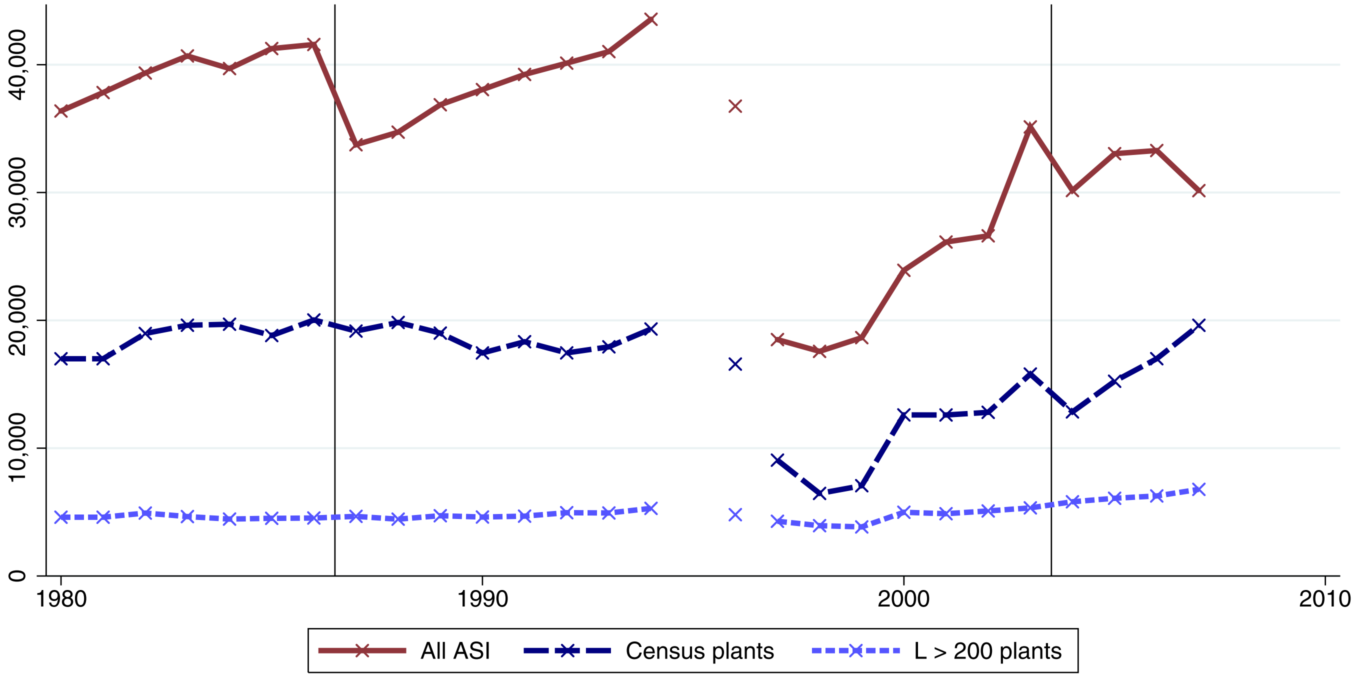

Fig. 3. ASI sample sizes. All open manufacturing ASI plants with positive factors of production and output are included. Years refer to beginning year of survey. Vertical lines indicate changes in sampling methodology in 1987 and 2004. Gaps indicate missing data in 1995 and anomalous data in 1996.

Table 1
ASI averages.

	All ASI	Census plants	$L \geqslant 200$ plants
Annual observations	33,741	16,181	4918
Employees per plant	89	294	814
Panel identification rate		79%	89%
Annual growth rate observations		10,404	3649

ASI manufacturing plants with positive factors of production and output 1980–1994 and 1997–2007.

between records on static variables such as location, and for "close" matches between year-end and year-start balance-sheet variables, such as opening and closing values of fixed assets. (See Appendix A for details about the plant matching algorithm.)

Table 1 presents a few statistics about three samples: all plants, Census plants and plants with 200 or more workers, respectively. The Census sample contains the largest number of linked-up plants, but Fig. 3 shows that its size jumps around disconcertingly over time. By contrast, the $L \geqslant 200$ sample reflects only the largest plants, which are always surveyed. The average ASI plant employs 89 people, whereas plants in the Census and $L \geqslant 200$ samples are much larger (employing 294 and 814 on average). We are able to successfully match 79% of annual records in the Census sample to previous-year records, and this rate rises to 89% for the largest plants. The remaining records represent plants that either entered or exited the Census sample, or were not matched due to measurement error. The final row shows that, once the plant match rate is taken into account, we are left with about 10,404 annual plant growth rate observations in the Census sample, and 3649 annual plant growth rate observations in the $L \geqslant 200$ sample.

4. Productivity growth: trends and decomposition

Fig. 1 provided preliminary evidence of rising levels and growth rates of labor productivity in Indian manufacturing (formal and informal), particularly from the early 1990s onwards. These trends are also visible when we focus on formal manufacturing. Using manufacturing totals from ASI plant-level data and economy-wide totals from the World Development Indicators, Fig. 4 plots manufacturing's share of economy-wide value added (GDP) and employment. Over the entire 1980–2007 sample, ASI manufacturing rose from about 13.5% to 17% of GDP. At the same time, ASI employment fell from 2.4% to 2.0%. Clearly, labor productivity growth in the ASI exceeded that in the rest of the economy. Moreover, the *level* of labor productivity is dramatically higher in ASI manufacturing than the rest of the economy. Fig. 1 above showed that manufacturing overall was a higher share of output than of employment, with labor productivity being twice as high in manufacturing as in agriculture. Implicit in Fig. 4 is that labor productivity is much higher in formal manufacturing than in informal manufacturing. See Hsieh and Klenow (2012) for direct evidence to this effect.

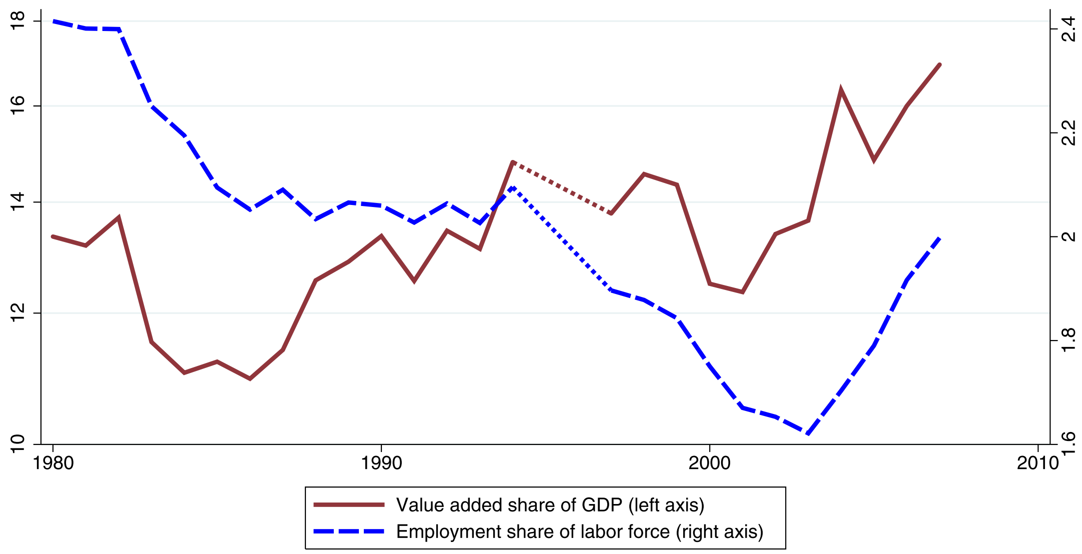

Fig. 4. ASI manufacturing shares of Indian GDP and labor force (%). *Sources:* GDP and labor force from World Development Indicators. Manufacturing totals from ASI micro data.

Table 2
Growth rates of annual aggregates, 1980–2007 (%).

	All plants	Census panel	$L \geqslant 200$ panel
Output	8.1	10.0	9.8
Value added	9.4	10.8	10.6
Fixed assets	8.8	9.2	8.8
Unskilled labor	1.6	3.0	2.6
Skilled labor	1.6	2.9	2.4
Total factor inputs	3.9	5.1	4.7
Aggregate productivity	5.4	5.8	5.9

Source: ASI—see Appendix A for panel construction details.

4.1. Estimated growth

With the ASI samples in hand, we now proceed to growth accounting exercises. The aggregate TFP growth outlined in Section 2 involves averaging plant-level growth rates of value added and inputs. But a common way to calculate aggregate TFP growth is to sum *levels* of value added and inputs across plants and then calculate growth rates from these aggregates. For robustness and comparability to other studies, we start with the growth rates of aggregates.

Table 2 reports annual rates of growth for aggregate gross output, value added and factor inputs in Indian manufacturing for the period 1980–2007. The three columns cover different samples: all plants in column 1 (including smaller sampled plants), the panel of Census plants in column 2 (those sampled with probability 1), and the panel of plants that employ 200 or more workers in column 3 (a subset of the Census panel plants). As mentioned in Section 3 and illustrated in Fig. 3, the $L \geqslant 200$ sub-sample is likely to be more reliable since these plants are always surveyed irrespective of changes in sampling methodology. Across the three samples, value added growth ranges from 9.4% to 10.8%, input growth ranges from 3.9% to 5.1%, and TFP growth ranges from 5.4% to 5.9%. TFP growth is modestly faster for the bigger plants, suggesting they contribute disproportionately to overall growth.

In Table 3 we look at the growth of aggregates in Indian manufacturing across two sub-periods: 1980–1992 and 1993–2007.[4] The table reports a substantial increase in the rate of growth of TFP across the two sub-periods. Using all ASI plants, the growth rate of TFP rose from 3.5% to 7.4% from 1980–1992 to 1993–2007 (columns 1 and 4). A sizable pickup of around 3 percentage points is also visible in Census plants (from 4.3% to 7.3%) and in the $L \geqslant 200$ plants (from 4.3% to 7.5%).

[4] We choose the year 1992–1993 as the break year for two reasons. First, in the context of the industrial and trade policy reforms that took place in 1991 (following a balance of payments crisis), it is interesting to compare the growth of the manufacturing before and after the early 1990s. Second, a dummy variable which switches on in 1992–1993 explains the largest fraction of the growth rate of TFP of any dummies near the midpoint of the sample. Here we regress aggregate productivity growth in year t on $ERA_t^p = 1$ if $t >= p$, $p = 1980, \ldots, 2007$. These results are available in an Online Appendix. Thus, the data locally prefer 1992–1993 as the year in which the break in TFP growth occurred. There is even stronger evidence of a break in 2002–2003. We return to this issue below.

Table 3
Growth of aggregates over two periods (%).

	1980–1992			1993–2007		
	All plants	Census panel	$L \geqslant 200$ panel	All plants	Census panel	$L \geqslant 200$ panel
Output	7.8	7.3	7.5	8.4	12.8	12.2
Value added	7.0	7.4	7.6	11.8	14.3	13.6
Fixed assets	10.1	9.0	9.0	7.4	9.3	8.6
Unskilled labor	0.5	0.4	0.6	2.7	5.7	4.5
Skilled labor	1.7	1.0	1.0	1.5	4.9	3.7
Total factor inputs	3.5	3.1	3.3	4.4	7.0	6.2
Aggregate productivity	3.5	4.3	4.3	7.4	7.3	7.5

Source: ASI—see Appendix A for panel construction details.

Table 4
Averages of plant-level growth rates, 1980–2007 (%).

	Census panel	$L \geqslant 200$ panel
Value added	6.9	7.4
Total factor inputs	0.2	0.3
Aggregate productivity	6.7	7.1
Plant efficiency	4.8	5.3
Within-sector reallocation	1.1	1.0
Between-sector reallocation	0.2	0.2
Aggregate profits	0.6	0.6

Source: ASI—see Appendix A for sample construction details.

Table 5
Averages of plant-level growth rates over two periods (%).

	1980–1992		1993–2007	
	Census panel	$L \geqslant 200$ panel	Census panel	$L \geqslant 200$ panel
Value added	4.2	4.4	9.6	10.4
Total factor inputs	0.2	0.3	0.3	0.3
Aggregate productivity	4.0	4.1	9.3	10.1
Plant efficiency	2.4	2.5	7.1	8.0
Within-sector reallocation	1.1	1.0	1.1	1.0
Between-sector reallocation	0.1	0.1	0.3	0.2
Aggregate profits	0.3	0.4	0.8	0.9

Source: ASI—see Appendix A for sample construction details.

4.2. Growth within plants vs. reallocation across plants

We now calculate plant-level growth rates of key variables then aggregate them using plant shares in aggregate value added. This allows us to decompose aggregate TFP growth into plant-level efficiency growth, between- and within-sector reallocation, and an aggregate profits term, as described in Section 2 above.

Table 4 shows that TFP growth averaged around 6.7% during 1980–2007 among Census plants in the ASI, and 7.1% among $L \geqslant 200$ plants. These TFP growth rates are modestly faster than those calculated on growth rates of aggregates (5.8% and 5.9%, respectively). The difference arises not on the output side (average plant output growth actually exceeded the growth of aggregate output), but rather on the input side (plant inputs grew little on average, whereas aggregate input use grew substantially).

The bottom portion of Table 4 reveals that the primary source of TFP growth is growing productivity of individual plants: 4.8% per year for Census plants and 5.3% for $L \geqslant 200$ plants. Reallocation of inputs from low to high productivity plants *within* three-digit industries contributed 1.1% annually among Census plants and 1.0% annually among $L \geqslant 200$ plants, whereas reallocation of inputs *across* three-digit industries contributed just 0.2% per year. Finally, because of very positive economic profits in the aggregate, even modestly growing input contributed 0.6% per year.

Table 5 shows that the growth speedup occurs when aggregating plant growth rates, just as when taking growth rates of aggregates. The TFP growth rate jumped from 4.0% to 9.3% for Census plants and from 4.1% to 10.1% for large plants (those with employment greater than or equal to 200) from the mid-1990s onward. Panel A of Fig. 5 illustrates the growth pickup visually. The figure makes it clear that TFP growth is volatile from year to year. This will show up in estimated standard errors shortly.

The bottom half of Table 5 decomposes the growth speedup. Most of the TFP growth speedup is attributable to rising plant-level efficiency (which saw a 4.7 to 5.5 percentage point jump between the sub-periods). Much smaller but

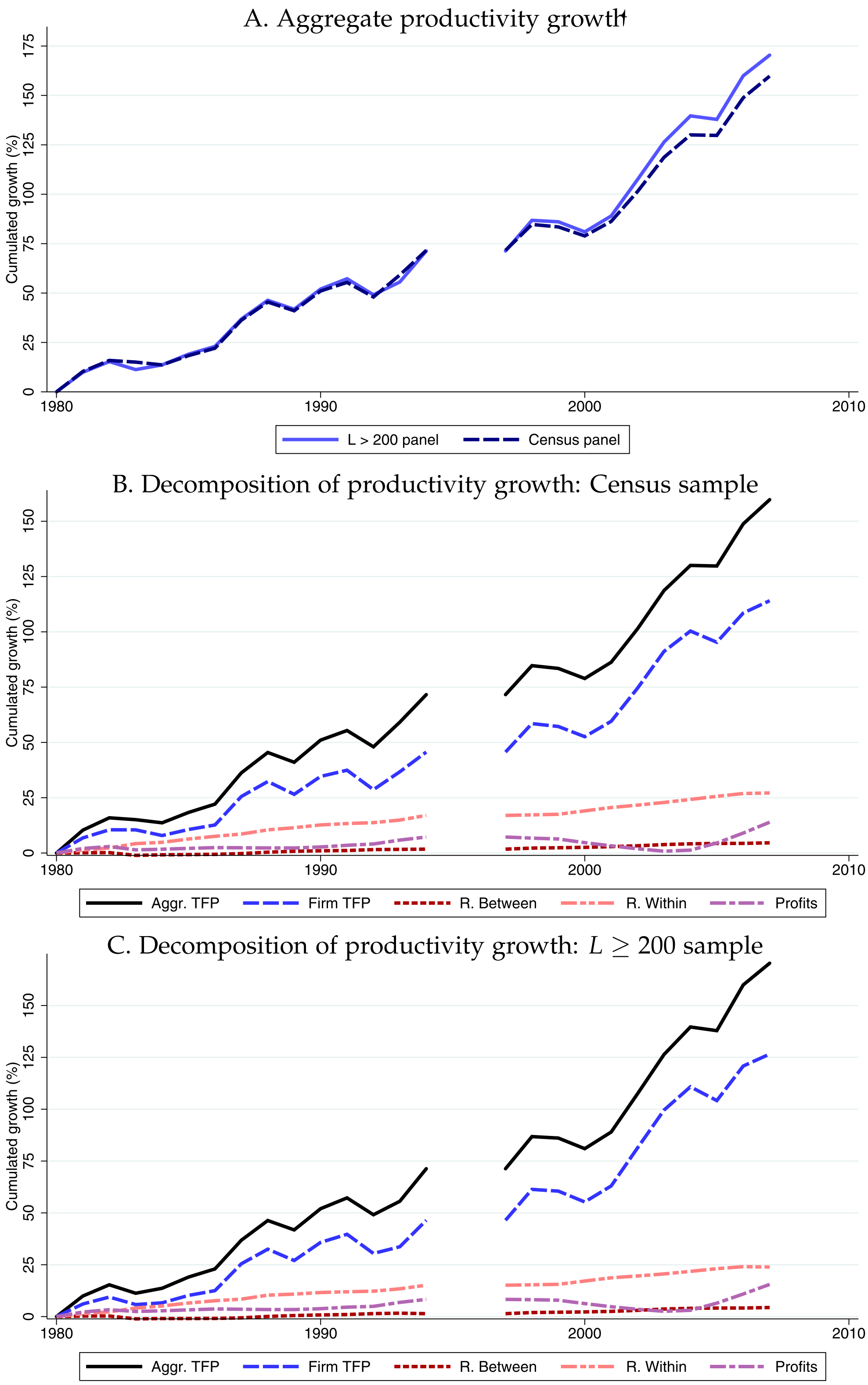

Fig. 5. Cumulative productivity growth and its components. Series re-initiated in 1997 at 1994 levels due to missing 1995 and 1996 data.

significant is the contribution of aggregate profits, which increased from around 0.3 to 0.8% per year. Within-sector reallocation continued at the same pace in the two sub-periods, at about 1.1% per year. This result is surprising given various industrial and trade policy reforms that occurred from the mid-1980s to early-1990s. One might have expected reforms to reallocate factors from less to more productive plants within industries. The reforms may have done so, but evidently did not contribute to a faster rate of TFP growth from within-sector reallocation in the second half of our sample. The table does indicate a slightly quicker pace of gains from *between*-sector reallocation, from 0.1% to 0.3% per year. But this is small in the context of a roughly 5–6 percentage point growth pickup.

Panels B and C of Fig. 5 plot the decomposition year-by-year for the Census plants and larger plants, respectively. The figure makes it clear that rising within-plant productivity accounts for the bulk of overall growth. But reallocation within industries has been a nontrivial source of growth, cumulating to around 25% higher TFP in 2007 than in 1980. Reallocation of inputs across industries contributed little.[5]

It is useful to compare our estimates of TFP growth to other studies of Indian manufacturing and industry. Our estimate of roughly 4% average annual TFP growth from 1980–1992 is higher than the 2.2% of Hulten and Srinivasan (1999) for a similar period. They use published ASI aggregates, but apply a double deflation method whereas we calculate real value added using a Divisia index. Our estimate is closer to the 3.2% of Unel (2003). For the later period, our TFP growth of 9–10% is much higher than the 4.7% estimated by Unel (2003). Our later sample of 1993–2007 does not overlap much with the 1991–1997 sample in Unel (2003), which could be particularly important given some high growth rates in the 2000s.[6] Lastly, Harrison et al. (2011) also use ASI unit-level data to calculate aggregate TFP and its components. Their sample (1985–2004) is similar to ours (1980–2007). Like us, they find relatively little growth from reallocation among existing plants. They estimate much lower TFP growth than we do, however—on the order of 25% rather than 165%. Most of this discrepancy appears to stem from their use of a gross-output based measure without Domar weights.

We now turn to statistical significance of the pickup in TFP growth. We regress the growth rate of TFP on a dummy variable that takes on a value of 1 for years from 1993 onwards. Table 6 reports the results for the $L \geqslant 200$ sub-sample of plants, and Table 7 for all matched Census plants. The 5–6 percentage point increase in annual growth, while large economically, is only marginally significant statistically in the first column of Panel A. The p-values are between 5 and 10% due to standard errors on the order of 3 percentage points. Note we can aggregate TFP growth to the annual level before running these regressions, or instead run regressions at the sectoral or plant level. The coefficients are identical, but the standard errors shrink somewhat, with significance mostly at the 5% level. In each case we cluster by year, in the sectoral case by sector as well, and in the plant case also by plant. Given the sizable standard errors, the most generous interpretation of column 1 in Tables 6 and 7 is that the data show a large but inexact jump in productivity growth starting around the mid-1990s.

In Panel B of Tables 6 and 7 we report the significance of the speedup in plant-level efficiency growth. As the standard errors are a little smaller and the growth pickup a little larger, these are more often significant at the 5% level. Panels C and D of the tables show that gains from reallocation are estimated more precisely; we are more confident there was no uptick in the pace of reallocation.

In columns 2–4 of Tables 6 and 7 we test for a growth speedup after making corrections for heteroscedasticity. While our motivation is to try to obtain more precise estimates of any pickup, these will also serve as robustness checks. We implement three alternative weighting schemes. First, given that plant-level data may be particularly noisy in some years, in column 2 we weight each year by the inverse of the cross-sectional variance of plant growth rates in that year.[7] Second, to mitigate the impact of sector-specific noise, in column 3 of Tables 6 and 7, we use FGLS techniques to estimate the time series variance of sectoral TFP growth around its sectoral mean, and use the inverse of that to weight each sector-year growth rate observation.[8] In column 4, we weight each observation by the inverse of both plant and sector noise.

As shown in columns 2–4 of Tables 6 and 7, correcting for noise gives modestly more precise estimates. The magnitude of our estimate of the productivity speedup bounces around a little, but our basic result continues to hold. That is, there seemed to be a large increase in productivity growth in Indian manufacturing starting in the mid-1990s of around six percentage points. This was typically significant at the 5–10% level, and occurred mainly at the plant level as opposed to via reallocation of inputs across plants.

We mentioned earlier that TFP growth also appeared to pick up around 2002. In an Online Appendix we provide versions of Tables 6 and 7 for the alternative sample break of 1980–2002 vs. 2002–2007. The speedup beginning in 2002 appears even larger than that in 1993, but is also less precisely estimated given our sample ends in 2007. Still, the pattern is similar whether we look at a 1993 break or a 2002 break: the growth rate of within-plant productivity growth increased sharply, whereas growth from input reallocation did not.

[5] The cumulative growth of TFP for the Census ($L \geqslant 200$) sample was 159.8% (170.4%) in 2007 and the growth due to within-sector reallocation was 27.2% (23.9%) in 2007.

[6] Rodrik and Subramanian (2004) use the Unel (2003) estimates for manufacturing from 1980–1997. Our sample extends seven more years, in which growth appears notably faster. Also, Rodrik and Subramanian mostly use data for the whole economy from Bosworth and Collins when arguing that TFP growth picked up in the 1980s and stayed high in the 1990s.

[7] The weight is $\frac{1}{E[Var_t(g_{it}-\hat{g}_t)]/N_t}$, where g_{it} is the growth rate of TFP of plant i and $\hat{g}_t$ is the average growth rate of TFP in year t.

[8] To apply the GLS technique, we regress the growth rate of TFP on the era dummy variable in an ancillary regression and obtain the corresponding residuals. Then we project the log of the square of those residuals on sector fixed effects as variance predictors. The predicted values from this regression are the variance estimates used to obtain the FGLS estimator. Finally, we re-estimate the pickup equation, but now weighting by the inverse of the variance estimate. Note that we can implement this technique using either plant-level or sectoral data, not annual data.

Table 6
Estimates of the pickup in productivity growth since 1993, $L \geqslant 200$ panel.

	Noise weighting			
	None (1)	Plant noise (2)	Sector noise (3)	Both (4)
A. Aggregate productivity				
Annual data	6.01	5.52		
	(3.21)*	(3.37)		
B. Plant efficiency				
Annual data	5.47	4.75		
	(3.13)*	(3.48)		
Sectoral data	5.47	4.75	4.74	3.68
	(2.63)**	(3.11)	(2.25)**	(2.39)
Plant data	5.47	4.75	5.96	5.09
	(2.63)**	(3.11)	(2.52)**	(2.72)*
C. Between-sector reallocation				
Annual data	0.12	0.13		
	(0.16)	(0.13)		
Sectoral data	0.12	0.13	0.20	0.24
	(0.16)	(0.13)	(0.08)**	(0.07)**
Plant data	0.12	0.13	0.15	0.18
	(0.16)	(0.13)	(0.08)*	(0.07)**
D. Within-sector reallocation				
Annual data	−0.05	0.02		
	(0.23)	(0.23)		
Sectoral data	−0.05	0.02	0.16	0.16
	(0.25)	(0.26)	(0.17)	(0.19)
Plant data	−0.05	0.02	−0.11	−0.07
	(0.25)	(0.26)	(0.24)	(0.27)
E. Aggregate profits				
Annual data	0.47	0.62		
	(0.69)	(0.85)		
Sectoral data	0.47	0.62	0.49	0.65
	(0.66)	(0.80)	(0.55)	(0.64)
Plant data	0.47	0.62	0.24	0.36
	(0.66)	(0.80)	(0.53)	(0.64)

The dependent variable is $100 * (\log TFP_{jt} - \log TFP_{jt-1})$. Heteroscedasticity-robust standard errors, clustered by year and sector in sectoral data, and by year, sector and plant in plant data. (In the annual data, conventional standard errors are substantially smaller.) All p-values evaluated from t-distribution with 19 degrees of freedom. Sectoral and plant data regressions weighted by Basu–Fernald aggregation weights.

* $p < 10\%$.
** $p < 5\%$.

The fact that reallocation within industries did not contribute importantly to either average growth or the speedup is surprising. According to Hsieh and Klenow (2009), gaps in productivity were large in India from 1987–1994, and in China the narrowing of such gaps from 1998–2005 added around 2 percentage points a year to growth.[9] In India, we find that productivity dispersion within industries did not fall over time as one would expect from diminishing returns combined with input reallocation. Fig. 6 presents the histogram of plant productivities in 1980, 1990, 2000 and 2007.[10] These are log levels relative to the industry means. The top graphs are for the Census panel, and the bottom graphs for the $L \geqslant 200$ panel. The kernel density lines are weighted by the value added share of each plant, and the histograms are unweighted. Table 8 presents standard deviations of log productivity, the log difference of productivity at the 75th vs. 25th percentiles, and the log difference at the 90th vs. 10th percentiles, with plants weighted by their value added shares. The consistent pattern is that plant productivity dispersion rose from 1980 to 2007, though the exact timing depends on the measure (S.D., 90/10 or 75/25), weighting, and plants (Census vs. $L \geqslant 200$ panel).

The rise in productivity dispersion is consistent with our earlier finding that Indian growth did not get a lift from reallocation of inputs from low to high productivity plants. But transitory dispersion in plant productivity is hard to capitalize on given the constraints of information and adjustment costs. So, was the increase in plant productivity dispersion persistent or transitory? Table 8 provides the serial correlation of plant revenue productivity (in logs, relative to the industry mean) in 1980–1981, 1990–1991, 2000–2001, and 2006–2007. The serial correlation rose from the early years to the later years; productivity differences became more persistent, not more fleeting. Again, this is surprising in that many of the reforms should have reduced persistent differences, leaving more transitory ones.

[9] On the other hand, Fernald and Neiman (2011) found a modest role for growing misallocation in Singapore's low growth.

[10] This is dispersion in "revenue productivity", or TFPR, in the terminology of Foster et al. (2008). Given the lack of plant-specific output deflators, revenue productivity is proportional to the value of the average products of labor and capital at a plant, not the plant's underlying technical efficiency. See Hsieh and Klenow (2009) for an elaboration of this argument.

Table 7
Estimates of the pickup in productivity growth since 1993, Census panel.

	Noise weighting			
	None (1)	Plant noise (2)	Sector noise (3)	Both (4)
A. Aggregate productivity				
Annual data	5.31	5.51		
	(2.87)*	(2.77)*		
B. Plant efficiency				
Annual data	4.73	4.44		
	(2.75)*	(2.84)		
Sectoral data	4.73	4.44	4.28	3.99
	(2.32)*	(2.59)	(1.74)**	(2.38)
Plant data	4.73	4.44	5.40	5.07
	(2.32)*	(2.59)	(2.30)**	(2.36)**
C. Between-sector reallocation				
Annual data	0.13	0.14		
	(0.14)	(0.13)		
Sectoral data	0.13	0.14	0.10	0.11
	(0.12)	(0.12)	(0.06)	(0.06)*
Plant data	0.13	0.14	0.08	0.09
	(0.12)	(0.12)	(0.05)	(0.05)*
D. Within-sector reallocation				
Annual data	−0.03	0.02		
	(0.22)	(0.20)		
Sectoral data	−0.03	0.02	0.19	0.23
	(0.23)	(0.23)	(0.22)	(0.24)
Plant data	−0.03	0.02	−0.01	0.04
	(0.23)	(0.23)	(0.22)	(0.25)
E. Aggregate profits				
Annual data	0.48	0.91		
	(0.71)	(0.90)		
Sectoral data	0.48	0.91	0.39	0.70
	(0.68)	(0.86)	(0.56)	(0.64)
Plant data	0.48	0.91	0.29	0.68
	(0.68)	(0.86)	(0.57)	(0.74)

The dependent variable is $100 * (\log TFP_{jt} - \log TFP_{jt-1})$. Heteroscedasticity-robust standard errors, clustered by year and sector in sectoral data, and by year, sector and plant in plant data. (In the annual data, conventional standard errors are substantially smaller.) All p-values evaluated from t-distribution with 19 degrees of freedom. Sectoral and plant data regressions weighted by Basu–Fernald aggregation weights.
* $p < 10\%$.
** $p < 5\%$.

Table 8
Dispersion of TFPR.

	1980	1990	2000	2007
A. Census panel				
S.D.	0.73	0.72	0.70	0.84
75–25	0.71	0.86	0.72	0.97
90–10	1.66	1.66	1.66	2.02
Serial correlation	0.68	0.62	0.69	0.80
N	11,025	11,088	3704	13,102
B. $L \geqslant 200$ panel				
S.D.	0.59	0.59	0.66	0.77
75–25	0.55	0.69	0.68	0.87
90–10	1.37	1.40	1.71	1.87
Serial correlation	0.62	0.60	0.67	0.74
N	3411	3398	2420	4706

Source: ASI—see Appendix A for sample construction details.

Perhaps the reason we do not see a big role for reallocation is that inputs did not move around across plants, say because of firing restrictions on large formal plants. This does not appear to be the case. Table 9 shows the standard deviation of input growth rates across plants. These growth rates are relative to the industry mean. The S.D. was calculated for each year, then we averaged across the 1980s (1980–1981 through 1989–1990), the 1990s, and the 2000s. The resulting S.D. varied between 16% and 24% depending on the plants included and the time period. This is weighted by plant value added, so it is not driven a tiny amount of inputs flying to and from small plants. So inputs moved around, but not in a way that closed productivity gaps.

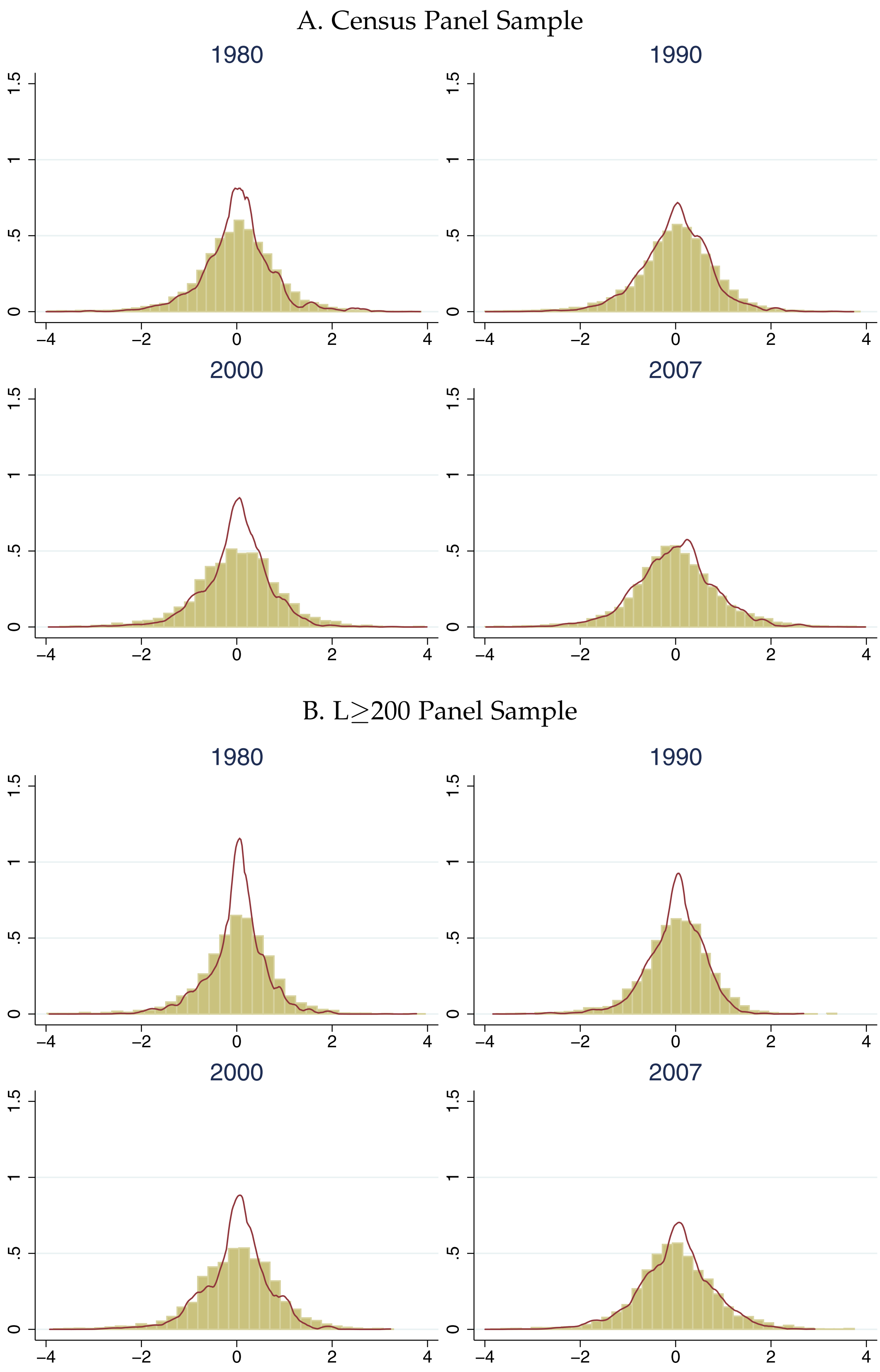

Fig. 6. Plant-level TFPR dispersion. Only the plants with positive weights are plotted. The line is the kernel density weighted by output share of each plant. The histogram shows unweighted frequency of plant-level TFPR.

Table 9
Dispersion of input growth (weighted).

	1981–1990	1991–2000	2001–2007
A. $L \geqslant 200$ panel			
S.D. of input growth	15.8	17.9	16.3
B. Census panel			
S.D. of input growth	18.4	19.5	18.5

Source: ASI—see Appendix A for sample construction details.

5. Reforms and productivity

We now ask: what caused the big increase in TFP in Indian manufacturing over our sample? The natural candidate is a series of industrial and trade policy reforms which began in the mid-1980s and intensified in the early 1990s. In Section 5.1 we provide details about these reforms and the mechanisms by which they might lift TFP either by promoting efficient input reallocation or within-plant productivity growth. In Section 5.2 we attempt to "explain" the productivity miracle, exploiting how the pace and timing of reforms varied across industries.

5.1. Industrial policy in India

After independence India adopted or continued industrial licensing, tariff and non-tariff barriers on imports, and restrictions on foreign direct investment. Later, a number of industries were "reserved" for small firms. Topalova and Khandelwal (2011), Sivadasan (2009), and Sharma (2008) provide details about the trade policy regime, the controls on FDI, and the license "raj", respectively. Panagariya (2008) provides a thorough review of the Indian growth experience and government policies. Below we provide a brief overview of some of the key policies and reforms affecting manufacturers.

The license raj refers to a system of controls on the entry of firms into the manufacturing sector commencing in 1956. Each and every plant that wanted to produce a manufactured good needed to receive permission (i.e., a license) from the central government. To receive a license, a plant had to satisfy certain conditions, including limits on output, imported raw materials, intermediate purchases, technology use, and the plant location.[11] The license regime arguably affected both the incentive and the ability of Indian plants to be productive. Complaints about the resulting high costs and low productivity in Indian manufacturing began building from the first decade of the licensing regime. But the first serious attempt to deregulate the system only came about in the 1980s. This was a piecemeal approach, in which a handful of industries were de-licensed in 1984, another handful in 1985 and so on. In 1991, the Indian economy faced a balance of payments crisis and received loans from the IMF and other international organizations. Under pressure from these organizations, the biggest de-licensing episode occurred. Almost all industrial licensing was removed—by 1994 all but 16% of manufacturing output had been de-licensed. Studies such as Sharma (2008) have linked de-licensing reforms to increases in the productivity of some plants, though there was no discernible impact at the industry level. De-licensing also appeared to raise the demand for skilled labor in Indian industry (Chamarbagwalla and Sharma, 2011), and may have contributed to growth differences across regions (Aghion et al., 2005, 2008). We use the same de-licensing measures as Chamarbagwalla and Sharma (2011) and Sharma (2008), updating for the years 2004–2007.

A number of studies have analyzed the complicated web of tariff and non-tariff barriers that were used to restrict foreign trade in the hopes of paving the way for national self-sufficiency. As Topalova and Khandelwal (2011) describe, the regime consisted of high tariffs, a complex import licensing system, an "actual user" policy that restricted imports by intermediaries, restrictions of certain exports and imports to the public sector, phased manufacturing programs that mandated progressive import substitution, and government purchase preferences for domestic producers. There were some attempts to liberalize the system in the late 1980s. It was the 1991 balance of payments crisis, however, that led to major changes in both tariff and non-tariff barriers. Non-tariff barriers were rationalized and scaled down. According to Topalova and Khandelwal (2011), 26 import licensing lists were removed and one "negative" list was established in its place. Harrison et al. (2011) document that, between 1991 and 1997, the average final goods tariff rate on manufactured products fell from 95% to 35%, and tariff harmonization occurred as well. That is, industries with the highest pre-reform barriers faced deeper trade reforms.

The rationalization of tariff and non-tariff barriers continued into the late 1990s and early 2000s. Das (2003), Topalova and Khandelwal (2011) and Harrison et al. (2011) analyze the impact of tariff and non-tariff barriers on productivity in Indian manufacturing. Using data on listed firms from 1987 to 2001, Topalova found that a 10% fall in tariffs lead to a 0.5% increase in TFP of the average firm. But Das did not find a positive impact of trade reforms on TFP at the industry level—in fact, he found productivity performance worsened as the pace of trade reform increased. In contrast,

[11] As Panagariya (2008) and Sharma (2008) discuss in detail, the purpose of licensing was to direct capital into desirable industries. Every five years, the Planning Commission would issue demand projections for various sectors and commodities. The Ministry of Industry was then supposed to allocate capacity via the licensing system in a way that was consistent with these projections. This meant that some plants were output-constrained at some point in almost all industries. That is, they wished to produce more but they were not allowed to do so.

Harrison et al. (2011) find *all* of their estimated average sectoral productivity growth can be explained by declining input tariffs. Harrison et al. (2011) are the main source of the tariff data we use in our analysis.

The third aspect of the industrial policy regime in India from 1970s onwards was control of foreign direct investment. As Sivadasan (2009) documents, prior to 1991 foreign ownership rates were restricted to 40% in most industries. Further restrictions were placed on the use of foreign brand names, remittances of dividends abroad, and imported content in output. After the 1991 balance of payments crisis, foreign ownership rates of up to 51% were allowed for a group of industries and the restrictions on brands, remittances and imported content were relaxed. Sivadasan (2009) estimates that this FDI liberalization boosted mean industry-level productivity by 22%, and that tariff liberalization boosted productivity by 59% (in the 1994–1995 period compared to the pre-reform 1987–1990 period). He found within-plant productivity gains were the single largest contributor, boosting TFP 25% in FDI-liberalized industries and 55% in tariff-liberalized industries. Intra-industry reallocation played a smaller role in the productivity gains he estimates. Sivadasan (2009) is the source of FDI liberalization data we use in our analysis.

The fourth and final Indian policy we analyze is the promotion of small-scale industry (SSI). In 1967 the government began a policy of reserving the manufacture of certain products exclusively for small producers (a plant was defined as "small" if its capital stock was under a certain threshold). Once a product was placed on the SSI list, no new medium or large enterprises were allowed to enter, and the production capacity of existing medium and large enterprises was capped. Panagariya (2008) points out that the bulk of SSI items were labor-intensive products, in which India presumably had a comparative advantage. SSI reservations may have kept India out of the world market for these products, and may have reduced the incentive of SSI plants to produce high-quality products. The SSI list began with 47 items but steadily expanded until tens of thousands of products were reserved. The market-oriented reforms of the 1980s and 1990s did not do much to dismantle this reservation. It was not until the early part of the twenty-first century that de-reservation of industries began in earnest.

5.2. *Policy regressions*

Each of the industrial and trade policy reforms that took place during the 1980s and 1990s had the potential to boost aggregate productivity. De-licensing could have given productive plants greater leeway to raise their market share. Further, de-licensing may have induced plants to invest more in raising their productivity, as they could more easily scale up production if they became more productive. Trade and FDI reforms could have increased aggregate productivity through a number of channels. Examples include reallocation as in Melitz (2003), endogenous innovation of incumbents as in Atkeson and Burstein (2010), and increased availability of high quality imported inputs as in Goldberg et al. (2010a). More controversially, the presence of FDI on Indian soil may have generated productivity spillovers from foreign-owned plants to competing domestic plants or to vertically related Indian suppliers/buyers. De-reservation of SSI industries could have reaped scale economies, reallocated inputs from less to more efficient plants, and promoted innovation.

While reforms were concentrated in the late 1980s or early 1990s, there was substantial variation in the intensity and timing of reforms enacted across industries. Table A.7 shows significant cross-sectional variation in de-licensing during the 1980s, in FDI liberalization during the 1990s, and in trade reforms and de-reservation during the 1990s and 2000s. Moreover, Table A.8 shows that industries differed a lot in their productivity growth rates from 1980–2007. Whereas TFP in the median three-digit industry grew 4.5 percent per year, the standard deviation is around 7 percentage points per year, and the inter-quartile range is about 6 percentage points per year. Did those industries experiencing bigger reforms exhibit higher TFP after the reforms hit them?

With this motivation in mind, we regress the log level of industry productivity (TFP) on five policy measures, controlling for both year and industry fixed effects. We run these regressions on levels with the idea that reforms may have had permanent effects on the level of productivity, but not its growth rate. De-licensing of the textile industry in 1991, for example, might show up in higher TFP levels in the textile industry in 1991 onwards (relative to other industries in those years and relative to the norm for that industry). The policies are measured as the fraction of industry output licensed (which lies between 0 and 1), the tariff rate (a 100% tariff corresponding to 1), the fraction of the industry open to FDI (between 0 and 1), the fraction of the industry not subject to SSI reservations (again, between 0 and 1), and the input tariff rate (weighted average nominal tariffs on sectors that supply inputs, where the weights are input–output coefficients).

We collect these results in an Online Appendix. In most cases the reforms do not have a statistically significant relation to industry productivity or its components (plant efficiency, reallocation, etc.). There are some notable exceptions where the effects seem large both economically and statistically. For example, fully opening an industry to FDI is associated with 14–32 percentage points higher sectoral TFP, with standard errors sometimes less than 10 percentage points. This is mostly via growth in existing plant efficiency. Freeing up a fully reserved industry, meanwhile, seems to *lower* sectoral TFP by inducing high productivity industries to shed inputs. That is, inputs move from high to low productivity sectors as de-reservation occurs.[12] Finally, lowering *input* tariffs goes along with 14–34 percentage points higher sectoral productivity (standard errors of 8–15 percentage points), predominantly through higher plant efficiency.

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[12] This negative response is from the between-sector reallocation term. This is distinct from the within-sector reallocation term, which involves reallocation of inputs within industries.

We further regress industry log productivity levels on all five reform variables simultaneously rather than one by one. Multi-collinearity is obviously a potential pitfall, especially given several reforms took place around 1991 in many industries. Still, statistical significance continues to hold for FDI liberalization (associated with higher plant efficiency), de-reservation (associated with *worse* allocative efficiency across sectors), and input tariff reductions (higher plant efficiency).

Of course, absence of evidence is not evidence of absence. The standard errors are sizable (tens of percentage points). We often cannot reject the hypothesis of substantial benefits of a reform through a number of channels. We therefore set aside the issue of statistical significance, and calculate the effects of policy changes between 1980 and 2007 (between 1985 and 2007 for tariffs) implied by the point estimates in our policy regressions. This presumes causality. As a robustness check, we also consider the impact implied by the coefficients plus one standard error. This seems quite generous, probability wise, in that we do this for all of the coefficients at once.

Table 10 reports these calculations. For example, opening up 37% of output to FDI between 1980 and 2007 was arguably responsible for an 8 percentage point increase in aggregate TFP over that period. If we add up the estimated effects of all the policy changes together, in this fashion, the point estimate is a cumulative 13 or 19 percentage point boost to aggregate TFP, depending on whether we look at the $L \geqslant 200$ or Census panel. If we simultaneously add one standard error to each of the policy effects, the combined boost is more substantial at 28% (Census panel) or 40% ($L \geqslant 200$ panel). Such productivity benefits are in line with previous studies of individual reforms.

As Fig. 7 shows, the context is around 165% points of cumulative TFP growth from 1980 to 2007 (160% in the Census panel and 170% in the $L \geqslant 200$ panel). The point estimates from the regressions in Table 10 therefore attribute less than one-fifth of cumulative TFP growth between 1980 and 2007 to policy reforms. Essentially none of this is through allocative efficiency. If we add one standard error to all coefficients, the share of TFP growth explained rises to about one-third. Still, most of India's manufacturing miracle appears remains mysterious.

Now, reformed industries could have had lower productivity growth to begin with. But we obtain similar results when we change the dependent variable from industry-year productivity *levels* to *growth rates*. Industry productivity trends apart from the reforms should be absorbed in the industry fixed effects when the dependent variable is industry productivity growth.

Another possibility is policy reforms do not affect industry productivity immediately, but rather with a lag. In additional robustness tests we allow policies from the last three or five years to affect productivity. For example, we measure tariff policy in 1993 as the average tariff in 1993, 1992 and 1991. Tables A.9 and A.10 show that the contribution of reforms to cumulative TFP growth rises to 20–39% when we allow for 3 year lags, and to 29–50% when we allow for 5 year lags. Thus, allowing for longer windows more than doubles the explanatory power of de-licensing, FDI and tariff liberalization, and de-reservation. Still, the point estimates leave most growth unexplained.

An important caveat is that, for our full 1980–2007 sample, we have only 2-digit industry deflators. It is possible that 3-digit reforms raise productivity at the 3-digit level, but also lower the 3-digit deflator. Having policy measures more disaggregated (3-digit) than our industry deflators (2-digit) could be attenuating our estimated policy effects. To gauge the potential importance of this bias, we estimate policy effects on the 1980–1994 sub-sample for which we have 3-digit deflators. The results are little affected: the contribution of policy continues to be small relative to cumulative productivity growth.

We think it is appropriate to end this section with a recap of caveats to our analysis:

- Empirical proxies for reforms are crude and incomplete. Enforcement may differ across industries and time.
- Reforms might not be implemented randomly with respect to an industry's productivity prospects. Struggling industries might be targeted or shielded.
- Measurement of real output and inputs is far from perfect. Plants may cease to under-report output or inputs after de-licensing. Quality and variety are notoriously difficult to measure (but see Goldberg et al., 2010a, 2010b, for efforts on the input and output side for India).
- General equilibrium forces can exaggerate or hide the gains when looking at the industry level. Skilled workers might move in or out of reformed industries, thereby affecting TFP in reformed industries more than aggregate TFP. Industries with rapid TFP growth may see declining relative prices, making it crucial to pick these up in industry deflators.
- Forward-looking behavior can mute or amplify gains around the years when an industry is reformed. Firms might undertake investments in intangible capital in anticipation of future reforms (or even at the height of reforms), with the TFP benefits not showing up until later. See Costantini and Melitz (2010).
- Growth in other sectors—say in human capital per worker or the service sector—may have fueled manufacturing's success. The wave of reforms may have triggered investments in skills or technology well in advance of their implementation in specific industries, with benefits reaped well afterward.
- Earlier policies protecting the manufacturing sector may have laid the groundwork by building a manufacturing base primed for a miracle.
- Our analysis covers only large formal manufacturing plants, to the exclusion of smaller and informal plants, as well as the non-manufacturing sectors (agriculture, services).

Table 10
Aggregate effects of policy reforms.

	Policy mean		Sectoral productivity		Technical efficiency		Between-sector reallocation		Within-sector reallocation		Aggregate profit	
	1980	2007	$\Delta \cdot \beta$	$\Delta \cdot (\beta + \sigma)$	$\Delta \cdot \beta$	$\Delta \cdot (\beta + \sigma)$	$\Delta \cdot \beta$	$\Delta \cdot (\beta + \sigma)$	$\Delta \cdot \beta$	$\Delta \cdot (\beta + \sigma)$	$\Delta \cdot \beta$	$\Delta \cdot (\beta + \sigma)$
A. $L \geqslant 200$ balanced panel												
Fraction de-licensed	0.000	1.000	4.8	9.8	0.4	5.1	0.0	0.5	−1.2	−0.1	0.5	2.1
Tariff fraction*	0.915	0.138	−6.2	−0.1	−3.7	2.4	1.3	2.0	−0.8	0.4	0.3	1.5
Fraction open to FDI	0.000	0.375	8.4	12.6	6.2	10.5	−1.2	−0.8	−0.4	0.3	−0.4	0.6
Fraction de-reserved	0.965	0.988	−3.3	−1.8	−1.4	−0.3	−0.5	−0.3	−0.4	−0.3	−0.3	−0.2
Input tariffs fraction*	0.450	0.160	15.3	19.7	18.6	25.2	−1.0	−0.7	0.1	0.9	−0.5	−0.0
All policies			18.9	40.2	20.1	42.9	−1.4	0.6	−2.7	1.2	−0.3	4.0
B. Census balanced panel												
Fraction de-licensed	0.000	1.000	−1.0	2.2	−5.4	−2.4	−0.8	−0.3	−0.0	0.8	−0.1	1.4
Tariff fraction*	0.940	0.149	−5.5	−1.8	−6.7	−2.4	1.6	2.1	−1.6	−0.8	0.1	1.0
Fraction open to FDI	0.000	0.348	7.5	11.0	5.2	8.3	−0.9	−0.6	−0.2	0.4	0.0	0.9
Fraction de-reserved	0.962	0.984	−1.8	−1.2	−0.3	0.1	−0.5	−0.3	−0.4	−0.3	−0.3	−0.1
Input tariffs fraction*	0.450	0.160	14.2	17.7	16.5	20.4	−0.6	−0.4	0.4	0.8	−0.6	−0.1
All policies			13.4	27.9	9.2	24.0	−1.2	0.6	−1.8	0.9	−0.9	3.1

Policy coefficients were estimated by regressing log levels of industry TFP on individual policy measures, controlling for both year and industry effects and with weight correction for both plant and sector noise. "All policies" coefficients were estimated by regression log levels of TFP on all five policy measures simultaneously. Mean policy variables in 1980 were weighted by 1980–1981 value added shares, and 2007 means by 2006–2007 shares.

* For tariffs, presenting means for 1985 and 2007, and $\Delta \cdot \beta - \Delta \cdot \sigma$.

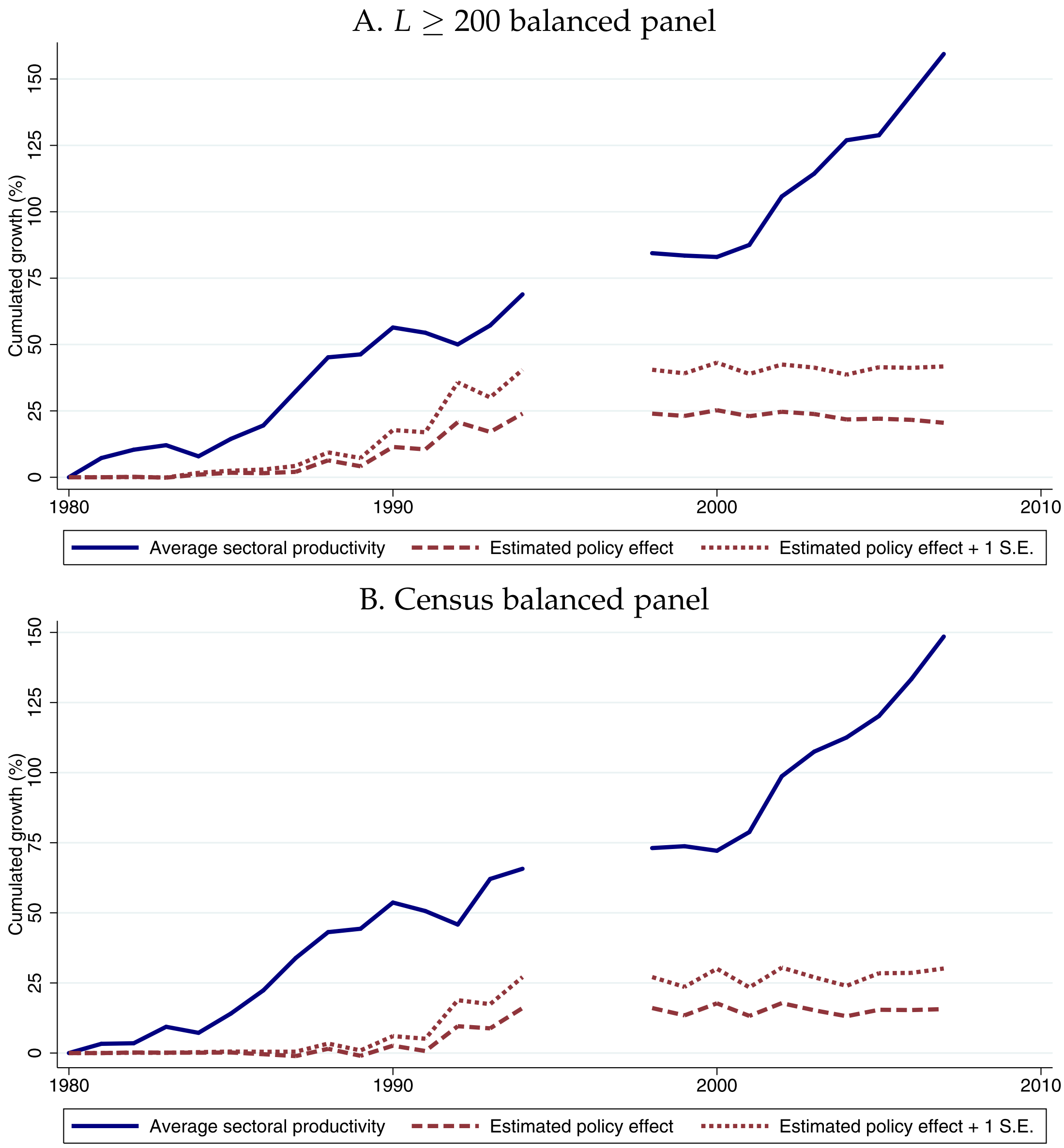

Fig. 7. Average sectoral productivity, and estimated policy contribution. "Estimated policy effect" plots the sum of cumulative aggregate changes in each policy multiplied by the effect estimated by regressing log levels of industry TFP on individual policy measures, controlling for both year and industry effects and with weight correction for both plant and sector noise. "Estimated policy-effect + 1 S.E." does the same, except it takes as it's "effect" the point estimate plus one standard error. Series re-initiated in 1997 at 1994 levels due to missing 1995 and 1996 data. All aggregate policy averages are weighted by the same annual value added shares used to aggregate productivity (1980 observations weighted by 1980–1981 shares, and 2007 policy observations weighted by 2006–2007 shares). Policy effect series differ slightly from totals in Table 10 due to missing 1994–1997.

It is clear from these caveats that looking at the industry-year level could easily overstate or understate the productivity effects of reforms.

6. Conclusion

Using the Annual Survey of Industries, we document a substantial speedup in manufacturing TFP growth in India: our point estimate is over 5 percentage points per year for 1993–2007 vs. 1980–1992. This estimate is imprecise, as the standard errors are 2.5 to 3 percentage points, depending on the exact correction for heteroscedasticity. Almost all of this pickup arises from changes in plant efficiency over time, as opposed to reallocation of inputs across plants.

As this rapid TFP growth occurred amidst a number of policy reforms in India, a natural question is whether reforms produced the manufacturing miracle. The truth may well be yes, but we could not confirm it. Those industries experiencing more liberalization (of licensing, tariffs, FDI, and size reservations) do not display sufficiently faster TFP growth to account for most of the miracle. Even if we raise all our policy impact estimates by one standard error at once, or consider several year lags for policy effects on productivity, these reforms account for less than one-third of cumulative TFP growth from 1980–2007, and none of the speedup.

Table A.1
ASI Census sample criteria.

1980–1981 to 1986–1987	100 or more workers 50 or more workers with power All plants in 12 industrially backward states
1987–1988 to 1996–1997	100 or more workers (with or without power) All plants in (same) 12 industrially backward states
1997–1998 to 2003–2004	200 or more workers Selected "Significant units" with fewer than 200 workers which "contributed significantly to the value of output" in ASI data between 1993–1994 and 1995–1996 All plants in (same) 12 industrially backward states All public sector undertakings
2004–2005	100 or more workers All plants in 5 industrially backward states

It is possible that liberalization made the miracle happen, but not in ways seen in measured growth at the industry level using our incomplete and imperfect reform indicators. This is our presumption. Our hope is that additional evidence on policies and productivity will clarify the role played by liberalization, which we very much presume to be positive.

Appendix A

A.1. ASI plant-level data

The ASI sampling population is all factories registered under Sections 2m(i) or 2m(ii) of the 1948 Factories Act: factories using power employing 10 or more (permanent, production) workers, and factories without power employing 20 or more workers. The Chief Inspector of Factories in each state maintains a list of registered factories, from which the ASI sampling frame is drawn.

All plants employing more than a threshold number of workers, along with plants in certain other categories, are surveyed each year—we call this the "Census sample". Smaller plants are sampled randomly. Table A.1 outlines how the Census sample criteria changed over the period of our data. An observation is single plant for the fiscal year from April to March, with the exception that an owner of two or more establishments located in the same state, industry group and survey division (i.e., Census sample or not) is permitted to submit a single consolidated return.

In Fig. A.1 we show the distribution of employment across all ASI plants and across plants in the Census sub-sample in 1980, 1990, 2000 and 2007. The distributions are quite similar across the samples and over time, move rightwards. Note that there exist Census sector plants with far fewer than 50 workers due to the fact that all plants in certain industrially backward areas needed to be sampled (see Table A.1).

Table A.2 shows the evolution of employment and real output across all three samples of the data and Table A.3 shows the distribution of employment across 2-digit industries and years.

A.2. Plant matching algorithm

The lack of plant identifiers in the ASI data is an econometric challenge. Fortunately, we know that data on plants in the Census sub-sample of the ASI are collected each year. Further the ASI data provide information on both time invariant plant characteristics—for e.g., year of initial production, state in which the plant is located, industry of operation etc.—as well as on opening and closing stocks of several accounting variables.

To link up annual plant observations into a panel, we algorithmically link up observations (in the Census sub-sample) in adjacent years pair-by-pair. To be matched, any two observations must be in the same state-by-industry cell (using 1975 state boundaries). Within each cell, we then attempt to find unique matches on the eight variables (which are reported on a consistent basis in every year from 1980–1994 and 1997–2007). There are two plant characteristics which we expect to remain constant over time: the year of initial production, and four plant ownership categories. We take one match variable as the interaction of these. (No other static plant characteristics are reported using the same definition in every year.) There are also six variables for which opening and closing values are available in every year: fixed assets, working capital, raw materials, outstanding loans, finished goods and semi-finished goods. We try to match closing values to the opening values in the next year, rounded initially to six significant figures. Zero or missing values are not used in the matching algorithm.

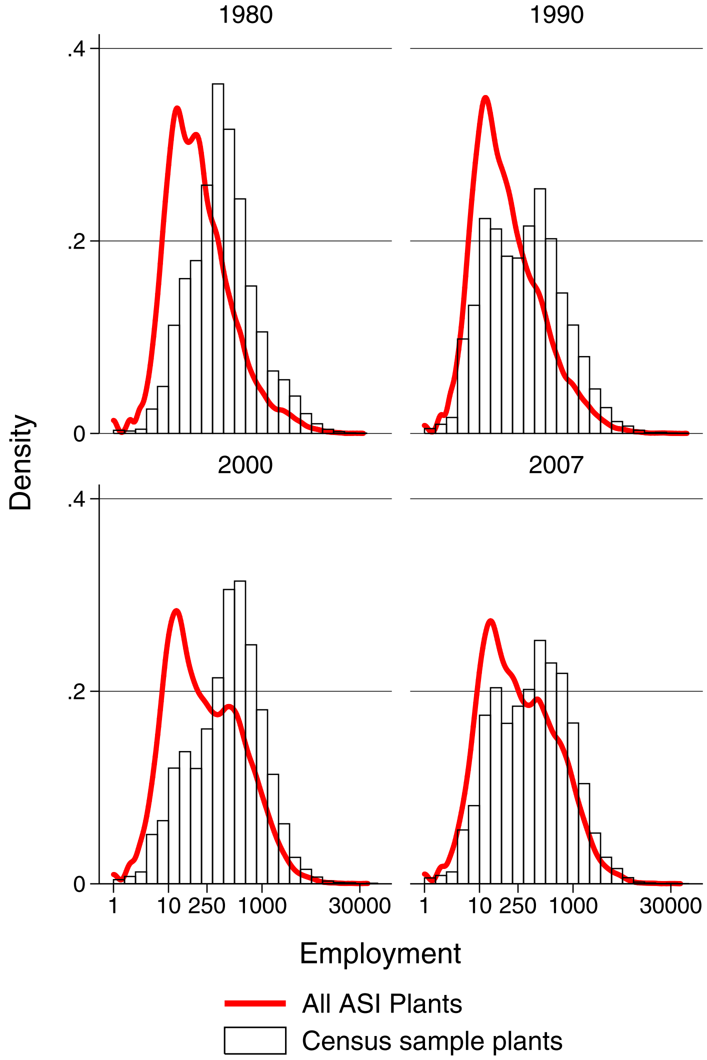

Fig. A.1. Distribution of employment in Indian manufacturing.

The algorithm proceeds as follows.

- For each year-to-year transition, within each state-by-industry cell, try to match observations which match uniquely on all seven matching variables.
- For the remaining unmatched observations, drop one matching variable at a time, starting with the variable with the most missing or zero values, and attempt to uniquely match on six matching variables.
- Iteratively continue, dropping more variables (in the same order). The minimum number of variables that are required to match (henceforth referred to as MV) is an important tuning parameter.
- Next, round all opening/closing variables to one fewer significant figure, and repeat the above. The minimum number of significant figures on each variable (henceforth referred to as SF) is the second important tuning parameter in the algorithm.

An additional complication arises due to the gap year 1995–1996 (when the survey was not conducted). We are unable to link plants with panel identifiers generated using the algorithm in 1994–1995 with those in 1996–1997. So the set of panel ids before 1994 do not carry over to observations after 1997. One interpretation of our strategy is that plants born in 1980 die in 1994 and then plants are reborn in 1997 with different identifiers. This inability to match the plants before and after the gap is exactly why we are missing the growth rates in 1995 and 1996 in all figures.

All analysis in this paper are based on plant data that are matched based on 3 variables (within the state-industry cell) and on a minimum of 2 significant figures. That is, $MV = 3$ and $SF = 2$. Below we explain our choice of tuning parameters. Fig. A.2 shows the distribution of employment across all ASI plants, across all Census sample plants and across plants that could be matched by our algorithm in various years. It is reassuring to see that the distributions are quite similar within each year.

Table A.2
Distribution of employment and output across Census and $L \geqslant 200$ samples.

Year	Employment (in millions)			Value added (billions)		
	All ASI	Census	$L \geqslant 200$	All ASI	Census	$L \geqslant 200$
1980	5.70	5.16	4.23	20.52	19.03	16.46
1981	5.77	5.20	4.23	22.73	21.17	18.36
1982	5.93	5.39	4.35	25.62	23.97	20.91
1983	5.65	5.08	4.05	23.48	21.77	18.50
1984	5.66	5.14	4.14	23.75	22.23	19.03
1985	5.45	4.88	3.84	25.88	24.42	20.92
1986	5.50	4.96	3.89	27.02	25.25	21.37
1987	5.31	4.82	3.98	28.17	26.37	23.09
1988	5.26	4.75	3.90	33.60	31.42	27.43
1989	5.36	4.76	3.91	35.33	32.69	28.66
1990	5.44	4.76	3.99	39.37	36.12	32.13
1991	5.44	4.74	3.93	37.31	33.70	29.49
1992	5.62	4.89	4.09	42.16	38.51	34.53
1993	5.55	4.77	3.96	42.73	38.33	32.81
1994	5.90	5.09	4.22	50.94	46.01	40.15
1996	5.22	4.51	3.75	38.72	33.35	27.12
1997	4.49	4.09	3.80	52.85	49.63	45.73
1998	4.23	3.76	3.58	57.70	53.12	50.04
1999	4.18	3.68	3.50	58.23	52.21	49.93
2000	4.76	4.38	3.77	61.86	58.06	51.31
2001	4.85	4.21	3.63	68.07	61.06	54.18
2002	4.93	4.28	3.67	77.94	69.97	63.00
2003	5.24	4.46	3.72	90.56	81.24	71.62
2004	5.16	4.58	3.97	112.37	105.20	97.01
2005	5.54	4.90	4.22	111.89	104.10	93.69
2006	5.82	5.20	4.48	129.44	120.99	109.89
2007	6.25	5.84	5.01	149.61	143.28	130.31

The table is constructed using ASI plants that were operating in each fiscal year and had positive factors of production and output. Employment is measured in millions of paid employees and value added in billions of 2005 US dollars.

Table A.3
Distribution of employment across 2-digit industries (%).

2-digit industry share of total employment					
NIC2	Description	1980	1990	2000	2007
20	Food products	13.0	9.4	9.5	8.0
21	Processed oils, fats, tea and coffee products	5.6	4.9	6.0	4.9
22	Beverages, tobacco and related products	4.0	7.3	9.4	6.9
23	Cotton textiles	16.8	12.4	7.9	5.9
24	Wool, silk, man-made fibre textiles	3.1	4.5	2.8	2.8
25	Jute and other vegetable fibre textiles	4.4	3.5	5.2	2.9
26	Textile products	1.3	1.9	5.0	9.8
27	Wood and wood products, furnitures and fixtures	1.4	0.8	0.7	0.6
28	Paper and paper products and printing, publishing and allied industries	3.9	4.0	3.2	3.0
29	Leather and fur and leather products	0.8	1.4	1.3	2.0
30	Chemicals and chemical products (excluding products of petroleum and coal)	6.8	7.9	9.8	8.8
31	Rubber, plastic, petroleum and coal products	2.4	3.2	3.9	4.4
32	Non-metallic mineral products	4.9	5.5	5.1	5.3
33	Basic metals and alloy industries	8.1	9.5	8.8	9.7
34	Metal products and parts, except machinery and equipment	2.9	2.8	2.4	3.6
35	Agricultural machinery and equipment other than transport equipment	5.8	6.1	5.3	5.1
36	Industrial machinery and equipment other than transport equipment	5.9	6.1	4.9	5.4
37	Transport equipment and parts	7.8	7.6	6.8	8.3
38	Other manufacturing industries	1.0	1.3	1.9	2.6

The table is constructed using ASI plants that were operating in each fiscal year and had positive factors of production and output.

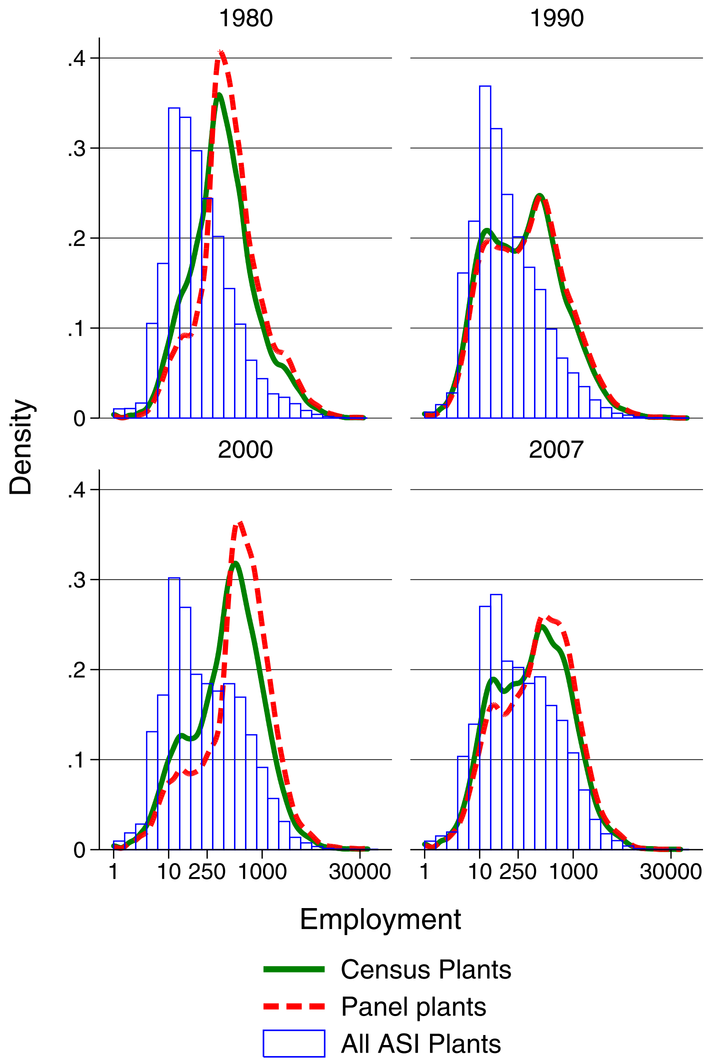

Fig. A.2. Distribution of employment in various samples.

Recently, the ASI has released plant-level data with plant identifiers for the years 1998–2007. This provides us with the unique opportunity of testing the quality of our matching algorithm. Tables A.4–A.6 show the Type I errors (i.e. real matches not identified by the algorithm) and Type II errors (of all pseudo-panel matches, those that are false positives) as well as the total number of matches. These tables guided our choice of $MV = 3$ and $SF = 2$ as tuning parameters. From these tables some important observations about our panel algorithm can be made.

- Even with the most lax criteria, a substantial number of matches are missed (e.g. Pr(Type I error) = 35%), which is trouble for the accounting of entry and exit using the pseudo panel.
- Due to data error (e.g., in the panel identified data there are instances of 'initial year' being misreported) no algorithm could attain 0% Type I errors.
- As expected, the criterion ($MV = 2$, $SF = 1$) incurs a high rate of false positives, but outside of the criteria (2, 1, 2, 2 and 3, 1) variation in the false positive match rate is under 1.3 percentage points.
- Using the strictest criteria ($MV = 7$, $SF = 6$), the loss in terms of correct matches foregone is high (only 4100 matches made).
- Although we presume that the cost of a false positive match is higher than the cost of a false negative for our analysis, the marginal rate of transformation would seem to justify relaxing criteria to some extent: with ($MV = 3$, $SF = 3$), the false positive rate increases by 1 percentage point relative to ($MV = 7$, $SF = 6$), but 36,000 matches are obtained versus 4100 (while false positives increase from 160 to 1800). Similarly, the criterion of ($MV = 3$, $SF = 2$) seems to us "better" than ($MV = 3$, $SF = 3$).

Table A.4
Type I error = % of real matches not identified by the algorithm.

SF	MV					
	2	3	4	5	6	7
1	28.5	32.9	40.7	51.6	68.3	86.8
2	30.6	36.2	45.4	57.6	74.3	90.2
3	31.6	37.9	47.7	60.6	77.2	91.8
4	32	38.6	48.8	62	78.4	92.5
5	32.3	39	49.4	62.7	79.1	92.9
6	32.6	39.7	50.2	63.8	80	93.3

MV = Minimum number of variables that need to match within a state-industry cell. SF = Number of significant figures required to match within each variable.

Table A.5
Type II error = % of algorithm matches that are false positives.

SF	MV					
	2	3	4	5	6	7
1	13.2	7.1	5.4	5.1	5	4.8
2	6.1	5.2	5	4.8	4.8	4.5
3	5.5	5.2	5	4.7	4.7	4.3
4	5.4	5.2	5	4.7	4.6	4.2
5	5.4	5.1	5	4.7	4.6	4.2
6	5.4	5.2	5	4.7	4.6	4.2

MV = Minimum number of variables that need to match within a state-industry cell. SF = Number of significant figures required to match within each variable.

Table A.6
Number of matches.

SF	MV					
	2	3	4	5	6	7
1	51,040	45,155	39,317	32,166	21,133	8889
2	46,187	42,152	36,117	28,097	17,080	6565
3	45,228	41,062	34,563	26,035	15,122	5486
4	44,936	40,594	33,847	25,128	14,299	4987
5	44,767	40,285	33,412	24,593	13,811	4735
6	44,532	39,869	32,882	23,927	13,200	4428

MV = Minimum number of variables that need to match within a state-industry cell. SF = Number of significant figures required to match within each variable.

A.3. Other data sources and methodology

All deflators come from the Reserve Bank of India's Handbook of Statistics on the Indian Economy. We use 2-digit output deflators together with a primary-sector deflator to construct industry-specific material deflators. To do this, we develop a concordance between our industry codes and the ASICC product codes reported for major inputs and outputs of each plant from 1996–1997 onwards, and then use the information on the value of input products to construct input–output tables. For each industry-pair we take the median input–output share for these years, and then use this information together with the manufacturing output deflators and a deflator for non-manufacturing primary-sector output to construct an industry-specific materials deflator as a weighted average.

Total compensation—including benefits, bonuses and any in-kind payments—is only reported for all employees, and so we assign all non-wage compensation between skilled and unskilled workers in proportion to the plant's wage payments to each of these groups. Fixed assets growth is calculated from the difference between opening and closing balance-sheet values.

Table A.7
Cross-sectional variation in reforms.

Employment de-licensed (%)							Employment FDI reformed (%)						
NIC2	1980	1985	1990	1996	2000	2007	NIC2	1980	1985	1990	1996	2000	2007
20	0	30	30.8	100	100	100	20	0	0	0	3.6	3.6	3.6
21	0	10	13.7	90	100	100	21	0	0	0	8.3	5.6	8.3
22	0	0	0	60	60	100	22	0	0	0	0.0	0.0	0.0
23	0	0	0	100	100	100	23	0	0	0	0.0	0.0	0.0
24	0	0	0	100	100	100	24	0	0	0	0.0	0.0	0.0
25	0	0	0	100	100	100	25	0	0	0	0.0	0.0	0.0
26	0	0	0	100	100	100	26	0	0	0	3.4	4.3	3.4
27	0	0	0	100	100	100	27	0	0	0	0.0	0.0	0.0
28	0	33.3	71.1	100	100	100	28	0	0	0	26.9	29.9	29.9
29	0	50.0	83.3	100	100	100	29	0	0	0	0.0	0.0	0.0
30	0	6.6	24.5	100	100	100	30	0	0	0	18.0	20.0	20.0
31	0	0.6	1.0	100	100	100	31	0	0	0	7.9	7.9	6.5
32	0	32.8	37.3	100	100	100	32	0	0	0	10.2	10.2	10.2
33	0	22.3	10.1	100	100	100	33	0	0	0	35.8	39.8	39.8
34	0	36.8	42.6	100	100	100	34	0	0	0	20.0	20.0	20.0
35	0	45.7	63.2	100	100	100	35	0	0	0	71.8	71.8	71.8
36	0	45.7	44.4	100	100	100	36	0	0	0	26.8	26.8	26.8
37	0	33.3	32.1	100	100	100	37	0	0	0	23.5	23.5	23.5
38	0	15.7	22.2	100	100	100	38	0	0	0	7.3	8.2	7.3

Average tariff (%)							De-reserved employment (%)						
NIC2	1980	1985	1990	1996	2000	2007	NIC2	1980	1985	1990	1996	2000	2007
20		88.0	89.7	37.0	38.0	29.1	20	87.9	87.9	89.1	87.9	96.7	96.9
21		112.9	112.2	39.2	38.1	43.2	21	88.6	88.6	86.4	88.6	100.0	100.0
22		123.2	140.6	94.2	68.1	59.2	22	100.0	100.0	100.0	100.0	100.0	100.0
23		72.5	72.5	43.2	31.0	13.8	23	0.0	0.0	0.0	100.0	0.0	100.0
24		97.1	95.8	50.8	30.1	10.9	24	99.9	99.9	100.0	0.0	0.0	0.0
25		89.0	70.0	46.4	36.5	10.6	25	0.0	0.0	99.9	0.0	99.9	0.0
26		97.9	103.2	51.2	34.8	11.2	26	94.5	94.5	94.5	94.5	94.5	100.0
27		79.0	68.9	34.9	37.2	11.3	27	90.1	90.1	90.1	90.1	90.1	93.9
28		56.3	68.9	20.4	20.5	7.6	28	89.4	89.4	89.4	89.4	90.6	96.1
29		92.0	94.0	41.7	33.5	11.3	29	80.9	80.9	80.9	80.9	80.9	100.0
30		98.9	104.3	41.2	35.8	10.5	30	93.4	93.4	93.4	93.4	93.5	96.0
31		78.7	84.5	39.9	32.4	10.5	31	90.7	90.7	90.7	90.7	91.0	99.6
32		83.9	96.3	48.5	36.7	10.4	32	97.8	97.8	97.8	97.8	97.8	98.8
33		105.1	99.9	29.4	34.4	6.6	33	99.2	99.2	99.2	99.2	99.2	99.6
34		121.1	163.0	39.0	37.6	11.2	34	92.5	92.5	90.7	90.7	92.6	95.5
35		66.4	86.1	32.9	27.2	9.1	35	92.7	94.0	94.4	94.0	94.0	100.0
36		95.2	108.6	40.7	28.4	7.3	36	97.8	96.5	97.8	97.8	97.8	98.5
37		71.7	77.1	41.7	33.0	15.5	37	97.4	97.4	97.4	97.4	97.4	100.0
38		83.3	91.6	40.6	34.3	10.9	38	88.5	88.5	88.5	88.5	88.7	96.2

For de-licensing, FDI reforms and de-reservation the columns show the percentage of employment within a 2-digit industry that was affected. De-licensing reform began in 1984 and FDI reform in 1992. Changes in reservation for SSI occurred sporadically throughout the period. Tariff data are not available prior to 1985.

A.4. Supplementary tables

Table A.8
Average annual industry TFP growth.

A. $L \geqslant 200$ panel	1980–2007
S.D.	7.36
90th percentile	9.49
75th percentile	6.79
Median	4.50
25th percentile	0.45
10th percentile	−3.58

B. Census panel	1980–2007
S.D.	7.34
90th percentile	8.64
75th percentile	6.44
Median	3.71
25th percentile	0.57
10th percentile	−3.65

Source: ASI—see Appendix A for sample construction details.

Table A.9
Aggregate effects of policy reforms (lag = 3 years).

	Policy mean		Sectoral productivity		Technical efficiency		Between-sector reallocation		Within-sector reallocation		Aggregate profit	
	1980	2007	$\Delta \cdot \beta$	$\Delta \cdot (\beta + \sigma)$	$\Delta \cdot \beta$	$\Delta \cdot (\beta + \sigma)$	$\Delta \cdot \beta$	$\Delta \cdot (\beta + \sigma)$	$\Delta \cdot \beta$	$\Delta \cdot (\beta + \sigma)$	$\Delta \cdot \beta$	$\Delta \cdot (\beta + \sigma)$
A. $L \geqslant 200$ balanced panel												
Fraction de-licensed	0.000	1.000	2.3	9.9	1.4	9.9	−1.5	−0.5	−1.7	−0.4	1.3	3.5
Tariff fraction*	0.915	0.138	−0.5	9.8	1.7	12.6	2.9	4.0	−1.6	0.2	1.7	3.6
Fraction open to FDI	0.000	0.375	13.7	18.7	8.8	13.6	−2.4	−2.0	−0.2	0.6	−2.9	−1.8
Fraction de-reserved	0.965	0.988	−4.9	−2.9	−3.0	−1.6	−0.8	−0.6	−0.4	−0.3	−0.4	−0.3
Input tariffs fraction*	0.450	0.160	27.7	39.2	33.3	47.0	−1.6	−0.8	1.1	2.5	0.6	2.1
All policies			38.5	74.8	42.2	81.5	−3.3	0.2	−2.8	2.6	0.3	7.2
B. Census balanced panel												
Fraction de-licensed	0.000	1.000	−8.8	−0.9	−13.3	−4.6	−1.9	−1.0	−0.4	0.4	−0.8	1.2
Tariff fraction*	0.940	0.149	−6.2	2.9	−6.6	2.6	3.5	4.1	−2.5	−1.4	0.9	2.2
Fraction open to FDI	0.000	0.348	13.9	18.3	11.8	15.7	−1.4	−1.0	0.3	1.2	−1.7	−0.8
Fraction de-reserved	0.962	0.984	−3.2	−2.2	−0.7	−0.2	−0.4	−0.3	−0.3	−0.3	−0.3	−0.2
Input tariffs fraction*	0.450	0.160	24.8	34.7	25.7	36.1	−1.0	−0.6	1.4	2.2	−0.1	1.0
All policies			20.5	52.8	16.9	49.7	−1.2	1.2	−1.5	2.3	−1.9	3.6

Policy coefficients were estimated by regressing log levels of industry TFP on individual policy measures, controlling for both year and industry effects and with weight correction for both plant and sector noise. "All policies" coefficients were estimated by regression log levels of TFP on all five policy measures simultaneously. Mean policy variables in 1980 were weighted by 1980–1981 value added shares, and 2007 means by 2006–2007 shares.

* For tariffs, presenting means for 1985 and 2007, and $\Delta \cdot \beta - \Delta \cdot \sigma$.

Table A.10
Aggregate effects of policy reforms (lag = 5 years).

	Policy mean		Sectoral productivity		Technical efficiency		Between-sector reallocation		Within-sector reallocation		Aggregate profit	
	1980	2007	$\Delta \cdot \beta$	$\Delta \cdot (\beta + \sigma)$	$\Delta \cdot \beta$	$\Delta \cdot (\beta + \sigma)$	$\Delta \cdot \beta$	$\Delta \cdot (\beta + \sigma)$	$\Delta \cdot \beta$	$\Delta \cdot (\beta + \sigma)$	$\Delta \cdot \beta$	$\Delta \cdot (\beta + \sigma)$
A. $L \geqslant 200$ balanced panel												
Fraction de-licensed	0.000	1.000	16.1	29.7	20.4	31.7	−1.5	−0.1	−3.7	−1.8	−0.3	2.7
Tariff fraction*	0.915	0.138	−8.2	6.7	−3.1	8.2	3.2	4.4	−2.7	−0.5	2.6	5.3
Fraction open to FDI	0.000	0.375	10.4	17.0	6.9	13.7	−3.0	−2.4	−0.8	0.2	−4.1	−2.8
Fraction de-reserved	0.965	0.988	−6.5	−3.9	−4.2	−2.3	−0.9	−0.9	−0.4	−0.3	−0.4	−0.3
Input tariffs fraction*	0.450	0.160	38.5	52.4	42.8	55.2	−1.0	−0.1	2.3	3.7	2.2	5.3
All policies			50.3	102.0	62.8	106.4	−3.2	0.9	−5.3	1.2	−0.1	10.1
B. Census balanced panel												
Fraction de-licensed	0.000	1.000	3.5	16.8	−4.3	5.5	−2.5	−1.7	−1.4	−0.1	−3.5	−1.1
Tariff fraction*	0.940	0.149	−17.7	−5.9	−12.3	−0.4	4.7	5.4	−2.1	−0.4	0.7	2.4
Fraction open to FDI	0.000	0.348	19.8	24.6	15.9	21.0	−1.8	−1.3	0.8	1.7	−3.5	−2.4
Fraction de-reserved	0.962	0.984	−3.5	−2.5	−1.3	−0.7	−0.6	−0.4	−0.4	−0.3	−0.4	−0.3
Input tariffs fraction*	0.450	0.160	27.1	38.9	21.6	33.4	−1.0	−0.3	2.2	3.5	2.5	5.3
All policies			29.3	71.8	19.7	58.8	−1.1	1.7	−0.9	4.4	−4.2	3.9

Policy coefficients were estimated by regressing log levels of industry TFP on individual policy measures, controlling for both year and industry effects and with weight correction for both plant and sector noise. “All policies” coefficients were estimated by regression log levels of TFP on all five policy measures simultaneously. Mean policy variables in 1980 were weighted by 1980–1981 value added shares, and 2007 means by 2006–2007 shares.

* For tariffs, presenting means for 1985 and 2007, and $\Delta \cdot \beta - \Delta \cdot \sigma$.

Supplementary material

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