

# Trade Liberalization and Productivity Growth: Evidence from Indian Manufacturing

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## Abstract

The impact of trade liberalization on productivity growth is still an empirical issue; the theoretical literature is as yet unclear on the direction of any such association. This paper develops an analytical framework and employs it to empirically test whether trade liberalization in Indian manufacturing has raised total factor productivity (TFP) growth. The answer is in the affirmative. The results also support a key postulate of the new growth theories, that liberalization of the intermediate-good sectors has a larger favorable impact on TFP growth than that of the final-good sectors.

## 1. Introduction

The impact of trade liberalization on productivity growth in the manufacturing sectors of developing countries remains a controversial issue. The conventional wisdom in favor of trade liberalization is that the latter can lead to significant gains in productivity. This view has, however, been challenged by the new theories of endogenous growth. The new growth theories do allow for the possibility that trade reforms may bring about a permanent change in productivity growth. However, these theories do not yield an unambiguous prediction on the direction of the change (Tybout, 1992). Given this ambiguity, the impact of trade policies on productivity growth is ultimately an empirical question.

However, the available empirical evidence on this issue has been far from conclusive—studies for developing countries that use firm- or industry-level data do not find an unequivocal positive relationship between trade reforms and productivity growth (Rodrik, 1995). Moreover, most of these studies have been plagued by both conceptual and empirical shortcomings. Firstly, the studies rarely pay attention to the *explicit* theoretical mechanisms through which trade policy may impact on productivity growth. As Rodrik (1995, p. 2935) notes, “since the conceptual issues are rarely sorted out as a prelude to empirical analysis, the hypothesized cause-and-effect are difficult to interpret.” In this paper, we explore the relationship between trade policy and productivity growth by identifying and testing two mechanisms by which trade policy may impact on total factor productivity growth. The first is the standard X-inefficiency argument that relates import competition to work effort on the part of workers. The second is trade acting as a conduit for access to specialized inputs, including capital, for production.

A second limitation of this literature is empirical in that there have been lack of reliable measures of trade policy changes (Edwards, 1993). In earlier studies that have investigated the link between trade liberalization and total factor productivity growth

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(such as Krueger and Tuncer, 1982), causality was attributed merely by association—if there was evidence that total factor productivity increased in the post-reform period, then it must be due to the reforms. More sophisticated analyses in the same vein that have used dummy variables to demarcate the post-reform period from the pre-reform one (e.g., Ahluwalia, 1991; Harrison, 1994) are open to the same criticism. More importantly, the use of dummy variables to measure trade reforms implicitly assumes (a) that the trade reform was a once and for all event, and (b) that it was complete. Neither of these two conditions may be satisfied in most trade liberalization episodes that one observes in developing countries (Michaely et al., 1991). The usefulness of dummy variables to capture trade policy shifts is greatly diminished if the trade liberalization has been gradual over time or if the reforms have been proceeding at an uneven pace across sectors.<sup>1</sup>

Other measures of trade policy that are common in the empirical literature are import penetration ratios and tariff-based calculations of effective rates of protection. The former is problematic in that significant trade reforms may affect productivity growth without being reflected in import volumes. On the other hand, while the effective rate of protection is a more direct measure of trade policy, its usefulness in empirical work is hindered by the unavailability of enough observations over time to undertake any meaningful econometric analysis. This paper uses a measure of trade policy that is less susceptible to the criticisms made of other measures and is also sufficiently informative in that it can capture changes in trade policy both across industries and over time. The measure is based on a comparison of the domestic and world prices of an industry—the “price wedge.” We also examine the role of intermediate- and capital-goods liberalization on productivity growth by measuring the greater access of firms to imported intermediate goods by an index of intraindustry trade in these goods.

The paper studies the effect of trade liberalization on the total factor productivity growth in Indian manufacturing using panel data on 30 industries over 1973–88. A case study of Indian manufacturing is particularly relevant for the issues at hand for two reasons. Firstly, a unique feature of trade reforms in India during this period has been that it has almost exclusively focused on the intermediate- and capital-goods sectors with little change in import controls on consumer goods imports. This enables us to test the role of intermediate-goods liberalization on productivity growth. Secondly, during this period, the Indian economy has witnessed a slow but steady liberalization of the trade regime pertaining to the manufacturing sector. This liberalization has by no means been complete and its progress has differed widely across different industrial sectors. Therefore, the Indian trade liberalization of the 1970s and 1980s does not lend itself to a straightforward before-and-after analysis.

## 2. Trade Policy in India

At the beginning of the 1970s, India had a highly restrictive trade regime. Nearly all imports were subject to discretionary import licensing or were “canalized” by government monopoly trading organizations. The only exceptions were commodities listed in the Open General License (OGL) category. Capital goods were divided into a restricted category and the OGL category. While import licenses were required for restricted capital goods, those in the OGL could be imported without a license subject to several conditions. Intermediate goods were divided into the banned, restricted, and

limited permissible categories plus an OGL category. As these names suggest, the first three lists were in order of import licensing stringency. The imports of consumer goods were, however, banned (except those which were considered “essential” and could only be imported by the designated government canalizing agencies).

Beginning with the export–import policy of 1977/78, there was a slow but sustained relaxation of import controls. Several capital goods that were not allowed to be imported without an import license were steadily shifted to the OGL category. The number of capital goods on the OGL list increased from 79 in 1976 to 1,170 in April 1988. These changes were made with the intention of allowing domestic industries to modernize and OGL status was usually accompanied by reduced customs tariff rates. Moreover, during the 1980s the import licensing of capital goods in the restricted list were administered with less stringency (Pursell, 1992). As a consequence, the import penetration ratio increased from 11% in 1976/77 to 18% in 1985/86 (Goldar and Renganathan, 1990). In the case of intermediate goods, too, there was a steady shift of items from the restricted and limited permissible categories to the OGL category. In most cases, the capital and intermediate goods placed on the OGL list were not being produced domestically. However, during this period, import liberalization may have led to an increase in competitive pressures on established producers of intermediate and capital goods as the goods that were allowed to be imported were, in several instances, imperfect substitutes of domestically produced goods (World Bank, 1989). The pace of the trade reforms—in particular, the shift from quantitative import controls to a protective system based on tariffs—initiated in the mid-1970s were considerably quickened by the new government (led by Rajiv Gandhi) that came into power in November 1985. Consumer goods remained on the banned list for the entire duration of the 1970s and 1980s.

To sum up, trade liberalization in India during the 1970s and 1980s was far from being comprehensive in its coverage or complete in its implementation. Yet the trade regime of the late 1980s was considerably more liberal than that of the early 1970s. The question we would like to ask then is: Did these reforms in trade policy have any effect on total factor productivity growth of the Indian manufacturing sector during this period?

### **3. The Analytical Framework**

The mechanics linking trade and productivity is as yet an open question in the theoretical literature, as noted previously. Here we employ two channels via which trade liberalization impinges on TFP growth. The first relies on the X-inefficiency literature where trade reform leading to increased international competition brings about a reduction in “slack” in labor input (Horn et al., 1996; Vousden and Campbell, 1994). The second channel via which trade reform raises productivity uses the “love of variety” formulation of Dixit and Stiglitz (1977), where access to a greater variety of specialized inputs raises TFP growth when these inputs are imperfect substitutes for one another (Romer, 1987). Here trade allows for specialization in the production of inputs; access to a greater variety of inputs through trade liberalization when each of these inputs is an imperfect substitute for the other raises total output. The simplest way to illustrate this point is to think of aggregate capital as comprising some finite number of specialized capital; trade policy impinges on access to the range of this specialized capital. The above two mechanisms are incorporated within the standard neo-

classical production function to deduce a reduced form that gives trade liberalization a role in growth.

Let the sectoral production function be of the form

$$Y = A(t)F(K^*, L^*), \tag{1}$$

where  $Y$  is output,  $A$  is an index of Hicks-neutral technological progress,  $K$  is the stock of physical capital, and  $L$  is labor input; an asterisk denotes the effective quantity of the factors used in production. We observe  $Y$ ,  $K$ , and  $L$ , where

$$K^* = U(R)K, \tag{2a}$$

$$L^* = E(R)L. \tag{2b}$$

$U$  is the utilization rate of capital, and  $E$  is an index for the quantity of effort put in by labor.  $R$  could be a vector comprising a host of variables that determine the level of effort put in by workers and the utilization rate of capital, but here we will confine ourselves to consider the role of trade only. Differentiating (1) after substituting in (2a) and (2b) gives

$$\hat{Y} = \hat{A} + s_K \hat{K} + s_L \hat{L} - \beta_1 \hat{R}, \tag{3}$$

where a circumflex denotes proportional change. If the production function in (1) is linearly homogeneous, then  $s_K$  and  $s_L$  denote factor shares, the sum of which should equal one.

Access to specialized inputs is the other channel via which trade liberalization impinges on TFP growth. Let  $K$  in equation (1) be an aggregate:

$$K = \left[ \sum_{j=0}^{\infty} \gamma_j k(j) \right]^{\frac{1}{\rho}}, \quad \sum_j \gamma_j = 1, \tag{4}$$

where  $j$  could, for example, be an index of the specificity and/or vintage of a particular type of capital. An analogous interpretation of  $K$  as being intermediate input can be made. A liberalization of the intermediate- and/or capital-goods sector would in the above framework have a positive impact on productivity growth. Now incorporating (4) into (3) gives an estimable equation of the form

$$\hat{Y} = \alpha_0 + \alpha_1 \hat{K} + \alpha_2 \hat{L} - \beta_1 \hat{R} + \beta_2 \hat{J}, \quad \alpha, \beta > 0 \tag{5}$$

where  $J$  denotes the number of intermediate inputs available at time  $t$ , the  $\alpha$  denote technology coefficients, and the  $\beta$  measure the responsiveness of output growth to changes in policy-related variables. A constant-returns-to-scale technology would imply that  $\alpha_1 + \alpha_2 = 1$ . Note that we use value-added ( $\hat{Y}$ ) as the dependent variable in testing for the effect of intermediate-goods liberalization on productivity growth instead of gross output ( $\hat{Q}$ ), as suggested by theory. However, to empirically implement such a formulation, we would need a measure of output that is gross of specialized intermediate inputs but *net* of raw materials. The unavailability of input-output coefficients for our sample of industries on a yearly basis does not permit us to compute such a gross output measure.

The literature on trade policy and TFP growth suggests that there are a number of channels via which trade policy can impinge on growth. The robust finding from all these specifications is that the association is negative as implied by (5) above. Controlling for growth of  $K^*$  and  $L^*$  in (5) gives an alternate specification of (5) as

$$\widehat{TFP} = \alpha_0 - \beta_1 \widehat{R} + \beta_2 \widehat{J}, \quad (5a)$$

where now TFP may be measured explicitly. The interpretation of the  $\beta$  coefficients are as follows:  $\beta_1$  measures the responsiveness of TFP to changes in protection via the factor markets, while  $\beta_2$  quantifies the response of increases in input-trade on TFP. The above two equations form the basis of the empirics that follow.

#### 4. Variable Construction and Data Description

##### *Quantifying Trade Policy*

In order to empirically implement equations (5) and (5a), we need to measure  $\widehat{R}$  and  $\widehat{J}$ . Note that  $\widehat{R}$  impinges on productivity growth by reducing the degree of slack that protection provides to domestic producers relative to their international competitors. Any such slack would be reflected as a positive deviation of the domestic price from the international price. Therefore, we measure protection by the “price wedge”—the deviation of the domestic price of the output produced by a particular industry from the world free-trade price for that industry.<sup>2</sup> We approximate the world free trade price of a particular industry by the price prevailing in the United States for that industry. Thus, we define the change in the protection rate,  $R_{it}$ , for industry  $i$  at time  $t$  as

$$\widehat{R}_{it} = \widehat{P}_{it}^{\text{INDIA}} - \widehat{P}_{it}^{\text{USA}} - \widehat{e}_t,$$

where  $P_{it}^{\text{INDIA}}$  and  $P_{it}^{\text{USA}}$  are the implicit price deflators of industry  $i$  at time  $t$  for India and the United States, respectively, and  $e_t$  is the exchange rate (Indian rupees per US dollar). The implicit price deflators, for a particular industry are obtained by deflating the industry’s value of production by the relevant quantity index. Therefore, according to our measure, protection increases in a particular industry in India if its domestic price increases relative to that of the US or if the nominal exchange rate depreciates.

The ability of the measure to reveal the “true level of protection” in a particular industry depends critically on the level of disaggregation at which the price deflators are computed. This is for two reasons. Firstly, the “price wedge” as a measure of protection is feasible only if the products compared are fairly homogenous in terms of their characteristics (Pritchett, 1996). The greater the level of disaggregation, the more similar is the industry’s product between the two countries. Secondly, in a highly complex trade regime as was the case in India, changes in trade policy have differed widely across industries. Aggregating over industries with disparate levels of protection can lead to a significant loss in the information content of our measure.<sup>3</sup> We compute the price wedge at the ISIC four-digit level (corresponding to the three-digit NIC level used in the classification of industry data in India), which is the maximum level of disaggregation that the data will allow.

There are two important limitations of our measure of trade policy. Firstly, while trade distortions should be reflected in a difference in *absolute* prices (i.e., unit values) of the commodity in question between India and the United States, we measure  $R$  as the difference in relative prices for a particular commodity between the two countries. The lack of data on volume of production at the ISIC four-digit (NIC three-digit) level from the Indian Central Statistical Organisation did not permit us to compute  $R$  using unit values. Secondly, changes in  $R$  should be impacted by factors other than trade policy, such as changes in product quality and transportation costs. However, as long

as the changes in trade policy are not overwhelmed by changes in quality or transportation costs, the  $\hat{R}$  measure would reflect changes in protection over changes in other factors.<sup>4</sup> Furthermore, we take into account the problem of measurement errors in  $\hat{R}$  in the econometrics that follow.

$\hat{J}$  measures the number of intermediate inputs available to domestic producers at a point in time. We use the Grubel and Lloyd (1975) index of intraindustry trade in intermediate goods to proxy for extent of trade in intermediate inputs.<sup>5</sup> Note that  $\hat{J}$  does not differ across industries. A limitation of this measure is that it captures policy outcomes rather than the policies themselves. As a robustness test of  $\hat{J}$ , we use protection data only for intermediate goods,  $\hat{R}_{\text{intermediates}}$ , as an alternate measure of trade policy changes with respect to the intermediate-goods sector.

### *Choice of Industries and Time Period*

Equations (5) and (5a) are estimated using panel data for 30 industries over the period 1973–88.<sup>6</sup> The choice of industries was dictated by the following two criteria:

1. The estimation of the two equations requires the availability of a satisfactory capital stock series for the period of the study. Aggarwal (1991) has constructed a capital stock series in constant prices for 42 of the largest industries in the Indian manufacturing sector using the perpetual inventory method.
2. To compute  $R$ , a precise mapping from the three-digit NIC classification system used in preparing industry data in India to the four-digit ISIC system of the US is necessary. This mapping was possible to implement for 30 of the 42 industries in Aggarwal's study. These were the final set of industries used in our study.

Our sample of industries covers approximately 20% of the total set of industries in the Indian manufacturing sector. Therefore, the possibility of a selection bias in the empirical analysis that follows cannot be discounted. However, these 30 industries were among the largest in India and accounted for 53% of gross value-added and 45% of total employment in the Indian manufacturing sector for the period 1973–88. Also, the 30 industries are divided in roughly equal proportions across the three major industry groups—consumer goods, intermediate goods, and capital goods.

With respect to the time period, we were interested primarily in evaluating the impact of trade reforms on TFP growth in India for the 1970s and 1980s—a period which witnessed significant changes in Indian trade policy. Nineteen seventy-three was chosen as the starting year of our analysis as there was a change in the classification and coverage of industries in that year which made industry data from the pre-1973 period noncomparable with later years. We ended in 1988 as there was another change in classification in some of the industries in our sample in the following year.

### *Basic Statistics*

In Table 1, we present estimates of  $\hat{R}$ , and total factor productivity growth for the three major industry groups, averaged over three nonoverlapping five-year periods: 1974–78, 1979–83, and 1984–88. Total factor productivity is computed using the Tornquist index formula. The table clearly indicates a significant acceleration in the rate of decrease in protection in the intermediate-goods and capital-goods sectors compared with the consumer-goods sector, in the period 1984–88. Therefore, the behavior of  $\hat{R}$ , the

Table 1. Changes in Protection,  $\hat{R}$ , and Total Factor Productivity Growth, TFPG, by Industry Classification<sup>a</sup>

	Consumer goods	Intermediate goods	Capital goods
$\hat{R}$ (%)			
1974–78	3.1	-2.3	-1.1
1979–83	-1.3	4.3	0.6
1984–88	-1.3	-8.0	-3.8
TFPG (%)			
1974–78	0.04	0.7	-2.2
1979–83	-1.3	-2.9	-0.9
1984–88	3.9	4.6	4.9

<sup>a</sup> Averages are weighted by share of industry in total output.

price wedge, for the industries in our sample seems to be in accord with our prior belief that the trade liberalization initiated in the Indian economy in the late 1970s has brought about a decrease in protection in the Indian manufacturing sector, especially in the intermediate- and capital-goods sectors. The ability of  $\hat{R}$  to capture changes in trade policy pertaining to the Indian manufacturing sector both across industries and over time provide some support for the use of the price wedge as an *indirect* measure of trade policy in the empirical analysis of section 5. The table also indicates that the decrease in protection seems to have coincided with a significant improvement in total factor productivity growth across all three industry groups in the period 1984–88 as compared with the two earlier periods—this is similar to what has been found by Ahluwalia (1991).

## 5. Empirical Analysis

In Table 2, we present the summary statistics of the key variables used in the regression analysis— $\hat{Y}$ ,  $\hat{K}$ ,  $\hat{L}$ , and  $\hat{R}$ .<sup>7</sup> The first column of the table reports the mean and the next two columns decompose the variance of each variable into its between-industry and within-industry estimates. We adopt the terminology conventionally employed by panel data studies: “between-industry” refers to the differences in industry-specific averages across industries, where the averages are computed over time, and “within-industry” refers to deviations of variables from these industry-specific means. We find that within-industry variation accounts for 90% or more of the total variance of each of the four variables in question. This indicates that studies that use measures of protection that are cross-sectional in nature (such as effective rates of protection) to decipher a negative relationship between protection and total factor productivity may not meet with much success in the Indian context.

To test the relationship between changes in protection and TFP growth noted in Table 1 more rigorously, we estimate equation (5) using panel data for the 30 industries in our sample over the period 1973–88. We employ the fixed-effects estimator to allow for intrinsic differences across industries with respect to the rate of technological progress. We use the standard procedure of sweeping out the fixed effects by trans-

Table 2. Summary Statistics

Variable	Mean	Variance	
		Between industry	Within industry
$\hat{Y}$	0.062	1.14	8.89
$\hat{K}$	0.068	0.19	1.87
$\hat{L}$	0.024	0.28	5.23
$\hat{R}$	-0.004	1.14	16.14

forming variables to deviations from their industry-specific means. An index of capacity utilisation,  $\hat{U}$ , is constructed so as to control for transitory shocks to productivity due to cyclical factors. We assume that the impact of changes in protection on output growth in manufacturing is equal across the component three-digit NIC industries. This assumption would be particularly valid in the event of complete factor mobility between these industries. The policy affected variables,  $\hat{R}$  and  $\hat{J}$ , are lagged by one year. This is done for two reasons. Firstly, changes in policy take time to impact on endogenous variables, so the one-year lag captures the first-order effects which are expected to be most pervasive. Secondly, lagging  $\hat{R}$  by one period precludes the possibility of reverse causality—that is, more efficient industries are liberalized earlier or faster. However, reverse causality could still occur if both productivity growth and changes in protection are serially correlated and a spell of productivity growth in a particular industry leads to a reduction in protection to that industry. If this is the case, we should expect to find that the errors in the estimated equations are serially correlated. We check for the possibility of serial correlation in the estimates below.

The results of the estimation are presented in Table 3.<sup>8</sup> Model 1 is an estimate of the Solow growth accounting identity, the rest are augmented with the variables as suggested in section 3. Model 2 is an estimate of equation (5). Model 3 uses protection data for the intermediate goods in place of the extent of intraindustry trade measure to check the robustness of the findings in the estimate for model 2. Model 4 decomposes the changes in protection into its constituent components: changes in domestic prices, changes in foreign prices, and changes in exchange rate.

The Durbin–Watson (DW) statistic indicates no evidence of serial correlation across all four models. The adjusted coefficient of variation is low for all the estimates, but is particularly low for model 1. The low coefficient of variation is not surprising given that estimates are for growth rates, panel data are used, and the fixed-effects procedure has been employed which employs dummy variables for each of the industries. We note that use of the OLS procedure gives an adjusted coefficient of variation of approximately 20% in the augmented models. If we use model 1 as the benchmark, then the augmented models are considerably better at explaining the variation in the data. Furthermore, the objective here is to investigate the role of trade liberalization in TFP growth; hence the ability of the model to explain the variation is not of primary concern.

The estimates of the technology coefficients in the augmented models are more plausible than in model 1. The assumption of constant returns to scale is not rejected in

Table 3. *Regression Estimates Employing the Fixed-Effects Procedure*

<i>Variable</i>	<i>Model 1</i>	<i>Model 2</i>	<i>Model 3</i>	<i>Model 4</i>
$\hat{K}$	0.17 (1.52)	0.30 (2.72)	0.25 (2.27)	0.31 (2.74)
$\hat{L}$	0.41 (6.03)	0.36 (5.51)	0.40 (6.02)	0.37 (5.37)
$\hat{U}$		0.12 (4.78)	0.11 (4.48)	0.12 (4.85)
$\hat{J}_{t-1}$		0.14 (2.16)		0.14 (2.01)
$\hat{R}_{t-1}$		-0.12 (-3.55)		
$\hat{R}_{t-1}$ (intermediates)			-0.21 (-2.76)	
$\hat{P}_{t-1}$				-0.14 (-3.58)
$\hat{P}_{t-1}^*$				0.066 (1.03)
$\hat{e}_{t-1}$				0.12 (0.95)
<i>DW</i>	2.17	2.10	2.20	2.19
Adjusted $R^2$	0.036	0.11	0.10	0.11
<i>SER</i>	0.0603	0.0577	0.0584	0.0579
Observations	420	420	420	420
No. of industries	30	30	30	30

any of the augmented models, though the point estimates suggest decreasing returns to scale. All of the  $\beta$  coefficients, the coefficient of interest to this study, have signs that are in accord with the theoretical priors. The estimates suggest that a rise in price distortion has a statistically significant negative impact on growth while a rise in extent of intraindustry trade in intermediate goods has a positive impact.<sup>9</sup> A comparison of the point estimates on  $\hat{R}$  in model 2 with those in model 3 suggests that liberalization of the intermediate-goods sector has had a larger impact on TFP growth relative to liberalization of all the sectors.

The point estimates of the individual parameters in the augmented models are statistically indifferent across the three models. The estimates suggest that, on average, a one percentage point rise in the price wedge leads to a 0.1 percentage point decline in TFP growth. This effect for the intermediate-goods sector is approximately double. The source of the negative coefficient on  $\hat{R}$  can be deduced by decomposing the variable into its constituent components. Before doing this we test the restrictions, as implied by  $R$ , that  $\hat{R} = \hat{P} - \hat{P}^* - \hat{e}$ , where  $P$  and  $P^*$  denote domestic and US prices, respectively. This restriction is accepted with a  $p$ -value on the  $F$ -statistic of 0.66. The decomposition of  $\hat{R}$  (model 4) suggests that it is the changes in domestic prices, rather than that in foreign prices or the exchange rate, that give rise to the negative and statistically significant coefficient on the protection variable.<sup>10</sup> Since this variable is impacted upon by policy, this provides further support for the view that changes in sectoral

domestic policies are the primary determinant of sectoral TFP growth. The point estimate of the responsiveness of TFP growth to changes in  $R$  is not large in magnitude, but it is the qualitative result that is of significance to the subsequent discussion. The finding that a reduction in the price wedge and the liberalization of the intermediate-good sectors has statistically significant impact on productivity growth is found in all of the estimates.

We examined the robustness of this finding by carrying out three further estimates. Firstly, imposing the statistically acceptable restriction of constant returns to scale on the parameters of  $\hat{K}$  and  $\hat{L}$ , we estimated equation (5a) where a direct measure of TFP growth using the Tornquist index formula is used as the dependent variable (model 5). We did this to control for the endogeneity of  $\hat{K}$  and  $\hat{L}$  arising out of their possible correlation with demand shocks included in the error term. Secondly, we used year-specific dummies in place of the industry-specific capacity utilization indices to incorporate temporary economy-wide shocks to productivity (model 6). Thirdly, we used data averaged over three-year nonoverlapping periods for a second estimate of equation (5) (model 7). By doing so, we control for the possibility that serially correlated exogenous supply shocks may bring about a spurious negative relationship between changes in domestic prices and productivity growth. By averaging over three years, we should be able to iron out fluctuations in the variables in question arising out of short-run shocks to the production function and domestic prices. These results are reported in Table 4. We find that, in all three estimates, there is no difference to our qualitative results, with the coefficients on the variables of interest retaining their correct signs and statistical significance. Again, there is no evidence of serial correlation in the estimated equations.

Next we account for the noisiness with which trade policy may have been captured by our sectoral relative prices. If changes in protection have been measured with error, ordinary least squares (OLS) in this case will give inconsistent parameter estimates. To test for the possibility of “errors in variables” in the regression estimates, we re-estimated equation (5) in two ways. Firstly, we used the instrumental variables (IV) method of estimation (and included industry fixed effects), where as an instrument of  $\hat{R}_{t-1}$  we used  $R_{t-3}$ .<sup>11</sup> Secondly, we replaced the price wedge with an alternate measure of protection—tariff-based estimates of the effective rate of protection (ERP). The ERP estimates are obtained from Goldar and Saleem (1992) and are available for only 23 of the 30 industries and for the years 1980, 1983, and 1989. We split the sample into pre- and post-1984 and replaced  $\hat{R}_{t-1}$  with the change in ERP ( $\Delta ERP$ ) between the years 1980 and 1983, and 1983 and 1989. This leaves two observations per industry—a total of 46 observations.

These two estimates are presented in the final two columns of Table 4 (models 8 and 9). We find the IV estimate of equation (5) in model 8 similar in pattern to the OLS estimate of the same equation (model 2 in Table 3), with the coefficients of  $\hat{R}$  and  $\hat{J}$  in model 8 corresponding closely to their counterparts in model 2 with respect to magnitudes and statistical significance. With the price wedge replaced by ERPs (model 9), the qualitative finding on the protection variable survives but the coefficient estimate is not statistically significant. The lack of significance of  $\Delta ERP$  is not surprising given that the aggregation over long periods and the averaging of annualized differences eliminates much of the time variation in the data (as we have observed in Table 2, much of the variation in the data is within-industry as opposed to between-industry).

Table 4. Robustness Tests

Variable	Model 5	Model 6	Model 7	Model 8	Model 9
$\hat{K}$		0.43 (3.34)	0.53 (2.49)	0.43 (3.67)	-0.09 (0.55)
$\hat{L}$		0.36 (5.02)	0.18 (1.38)	0.09 (0.06)	0.81 (3.45)
$\hat{U}$	30.65 (5.50)			0.11 (3.96)	0.30 (2.02)
$\hat{J}_{t-1}$	41.98 (2.80)		0.52 (1.51)	0.18 (2.61)	-0.01 (0.04)
$\hat{R}_{t-1}$			-0.13 (-2.11)	-0.16 (4.03)	
$\Delta ERP_t$					-0.05 (0.68)
$\hat{P}_{t-1}$	-43.48 (-4.91)	-0.097 (-2.22)			
$\hat{P}_{t-1}^*$	14.48 (1.00)	0.082 (1.17)			
$\hat{e}_{t-1}$	9.20 (0.32)	0.91 (0.21)			
Estimation method	OLS	OLS	OLS	IV	OLS
DW	2.12	2.10	—	—	—
Adjusted $R^2$	0.05	0.09	0.01	0.09	0.05
SER	13.26	0.0586	0.0258	0.0596	0.0427
Observations	420	420	120	390	46
No. of industries	30	30	30	30	23

Notes: Model 5 has *TFPG* as dependent variable. Model 6 uses year dummies in place of capacity utilization indices. Model 7 uses data averaged over three-year nonoverlapping periods. Model 8 is an IV estimate of model 2. Model 9 replaces  $\hat{R}_{t-1}$  with  $\Delta ERP_t$ .

## 6. Conclusions

The question investigated in this paper has been whether trade reform in Indian manufacturing has had a positive impact on TFP growth. The answer is in the affirmative and is robust to several sensitivity tests. The two secondary findings of the paper include the demonstration of a simple method of testing the hypothesis that a rise in availability of specialized inputs raises TFP growth, and an illustration of use of a price wedge as an alternative measure of the extent of protection.

The case of Indian manufacturing for the examination of the central hypothesis of this paper is suitable for the following reasons. First, the reform process in India has been gradual, so that a before-and-after analysis is not suitable. Second, Indian reform with respect to the final- and intermediate-goods sectors has been different, allowing for the examination of the hypothesis that the liberalization of the intermediate-good sectors is more important than that of the final-goods sectors for TFP gains. Third, data on variables of interest are available (albeit for a limited number of industries) in published form.

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## Notes

1. Furthermore, dummies may capture changes in policy unrelated to the trade regime or exogenous developments in the geopolitical world.
2. As Harrison (1996, p. 421) notes, "price comparisons between goods sold in domestic and international markets could provide an ideal measure of the impact of trade policy."
3. To take two examples, consider the three-digit ISIC industries—Electrical Machinery (383) and Transport Equipment (384). In the first case, audio and video equipment (ISIC 3832)—a

consumer goods industry—is clubbed together with several capital-goods industries, such as electrical industrial machinery (ISIC 3831) and insulated wires and cables (ISIC 3839). Similarly, in the second case, another consumer-goods industry, motor vehicles (ISIC 3843), is clubbed together with other capital-goods industries, such as railroad equipment (ISIC 3842). As we have already noted, Indian trade policy with respect to capital goods has differed significantly from that with respect to consumer goods.

4. To see this, define the price wedge,  $R$ , as  $R = PQ/eP^*Q^*$ , where  $Q$  denotes quality and an asterisk denotes foreign variables. In log-first difference, we obtain  $\hat{R} = (\hat{P} - \hat{e} - \hat{P}^*) + (\hat{Q} - \hat{Q}^*)$ . The second term has to be larger than the first to enable changes in  $R$  to be converse of quality-controlled prices.

5. This is the common empirical practice in the literature; see Backus et al. (1992).

6. The industries are: *consumer goods*—dairy products; grain milling; sugar refining; hydro-generated oils; cotton spinning and weaving; textile garments; paper, pulp and paperboard; drugs and medicines; perfumes and cosmetics; electric lamps; audio and video equipment; motor vehicles; *intermediate goods*—cotton ginning; tanning of leather; tire and tube industries; industrial organic and inorganic chemicals; fertilizers and pesticides; paints and varnishes; turpentine, synthetic resin, etc.; cement, lime and plaster; iron and steel; foundries for casting iron and steel; *capital goods*—hand tools; agricultural machinery; prime movers, boilers, etc.; industrial machinery for food and textile industries; general-purpose nonelectrical machinery; electrical industrial machinery; insulated wires and cables; railroad equipment.

7. Since  $\hat{J}$  does not differ across industries, we have omitted the latter in our summary statistics.

8. If the industry-specific effects are random and uncorrelated with the explanatory variables, then estimating a fixed-effects model using OLS will be unbiased but not as efficient as generalized least squares (GLS) estimates. Since the coefficients and standard errors for the GLS estimates were close to the within-industry estimates, the GLS results are not reported here.

9. We also experimented with introducing additional lags of  $\hat{R}$  and  $\hat{J}$  in models 2 and 3, with no change in the qualitative results.

10. We have used the official exchange rate in the construction of  $R$ . Given that India had currency controls during the period of the study, it could be argued that the black market exchange rate would reflect better the “true” home-price of the foreign currency than the official rate. However, when we substituted the black market rate for the official rate, we obtained far weaker results for  $R$ . This may be due to the fact that movements in the black market exchange rate in India may be driven by factors other than the trade and payments regime, such as the extent of smuggling in gold (see *World Currency Yearbook 1988–89*, pp. 444–5).

11. As shown by Griliches and Hausman (1986), if a variable  $x$  is measured with error, then, under the assumption of no serial correlation in the measurement error, noncorresponding adjacent  $x$  levels are valid instruments of the  $x$  difference.