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IS SKILL–BIASED TECHNOLOGICAL CHANGE HERE YET?
Evidence from Indian Manufacturing in the 1990s[1]

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ABSTRACT

Most high and middle-income countries showed symptoms of skill-biased technological change in the 1980s. India – a low income country – did not, perhaps because India's traditionally controlled economy may have limited the transfer of technologies from abroad. However the economy underwent a sharp reform and a manufacturing boom in the 1990s, raising the possibility that technology absorption may have accelerated during the past decade. We investigate the hypothesis that skill-biased technological change did in fact arrive in India in the 1990s using panel data disaggregated by industry and state from the Annual Survey of Industry (ASI). These data confirm that while the 1980s were a period of falling skills demand, the 1990s showed generally rising demand for skills, with variation across states. We find that increased output and capital-skill complementarity appear to be the best explanations of skill upgrading in the 1990s. Skill upgrading did not occur in the same set of industries in India as it did in other countries, suggesting that increased demand for skills in Indian manufacturing is *not* due to the international diffusion of recent vintages of skill-biased technologies.

1. INTRODUCTION

The Indian economy grew at unprecedented rates in the late eighties and nineties with manufacturing growth exceeding that of the rest of the economy. Rapid economic growth raises questions about what the Indian labor market will look like in the near future. If the experience of developed countries over the past few decades is any guide, demand for education will increase substantially. Predicting this demand is important, both because of the practical need to guide investments by individuals and institutions and because accelerated demand for education not matched by a matching surge in supply will lead to increased income inequality.

A growing consensus among labor economists is that a major factor leading to increased demand for education in the U.S. is the bias of technological change toward more educated labor, so called "skill-biased" technological change (SBTC). Autor and Katz (1999) provide a survey of this literature. Several authors have extended this conclusion to other OECD countries, including Katz, Loveman and Blanchflower (1995) and Berman, Bound and Machin (1998). Berman and Machin (2000) provide evidence of SBTC in manufacturing industries of middle-income economies as well, suggesting that SBTC could be a global phenomenon. Trade liberalization may be associated with SBTC in developing countries. For example, Pavcnik (2002) and Attanasio et al (2004) provide some evidence that imported technology adoption and trade are related to skill upgrading in Chile and Columbia respectively.[3]

Motivated by evidence of skill-biased technological change (SBTC) in middle income and OECD countries in the 1980s, we look for SBTC in Indian manufacturing in the 1980s and 1990s. In the Berman and Machin (2000) sample it appeared to be conspicuously absent in the 1980s in India. Yet, India's traditionally controlled economy underwent a sharp reform in 1991, suggesting the possibility that technology absorption may have accelerated during the past

decade. We investigate the hypothesis that skill-biased technological change did in fact arrive in India in the 1990s, examining Indian registered manufacturing using the Annual Survey of Industry (ASI). We look for symptoms familiar from the manufacturing sectors of other industrialized and developing countries.

We use the ASI for 1984-1998, aggregated by 3 digit industry for each of the twenty one Indian states and union territories. Our analysis of these data show that the mid- to late 1980s were indeed a period of falling demand for skilled labor in manufacturing, as reported in the cruder data used in Berman-Machin (2000). This is true to a varying degree in most Indian States. However, following major economic reforms in the late eighties and early nineties, the demand for skilled labor in manufacturing increased throughout the subsequent period, fairly consistently over time, though not consistently across states.

The pattern of changes in the demand for skill in Indian manufacturing is different from that observed for other countries in two important respects. First, though we do find some evidence of increased capital-skill complementarity, the best predictor of skill-upgrading is increased output. Second, previous studies find skill upgrading in manufacturing tends to be concentrated in the same industries across countries. Indian manufacturing did *not* undergo disproportional skill upgrading in those typical industries, indicating an increased demand for skill in manufacturing qualitatively different from that experienced by other OECD and middle-income countries.

2. THE INSTITUTIONAL CONTEXT

Indian industrial policies were put in place just after independence in the 1950s and remained largely unchanged until the mid-eighties. The Industries Development and Regulation Act of 1951 and the Industrial Policy Resolution of 1948 outline these policies. Their major objective was to achieve economic self-reliance through import substitution and large-scale public investment in heavy industry. Investment by private firms was governed by strict licensing requirements to ensure that the resulting pattern of production was in line with the priorities set out in the Five Year Plans.

In addition, the Monopolies and Restrictive Trade Policies (MRTP) Act of 1969 and the Foreign Exchange Regulation Act of 1973 were introduced to limit foreign equity in Indian industry and discourage market concentration. Statements of changes in industrial policy were made in 1973, 1977 and 1980 which involved some streamlining of the licensing process and additional advantages for small and medium sized firms, especially those which exported most of their production. No significant liberalization measures were taken before the mid-1980s.[4] Most firms required licenses for any capacity expansion or changes in their product mix. Foreign equity was severely restricted. Foreign exchange restrictions, import quotas and tariffs on both consumer and capital goods were used to encourage the growth of indigenous heavy industry.

In 1985 the regulatory framework started to change considerably. Clearances required for capacity expansion were reduced and industrial categories were broadened so that firms would not need approval for small changes in their product mix.[5] Each successive year shortened the list of industries requiring licenses. These changes were accompanied by a significant acceleration in the growth of manufacturing, which, for the first time since Independence, averaged over 6 per cent in the second half of the 1980s and almost 7 per cent between 1992 and

1997. Table 1 illustrates the acceleration of manufacturing growth and GDP growth in general in India since the early 1980s.

Table 1: Historical Sectoral Growth Rates in India

PLAN	Agriculture	Manufacturing	GNP
FIRST (1951-56)	2.5	5.0	3.7
SECOND (1956-61)	2.2	4.5	4.2
THIRD (1961-66)	-.30	5.3	2.8
Three Annual Plans (1966-69)	4.5	2.7	3.9
FOURTH (1969-74)	1.3	1.8	3.4
FIFTH (1974-79)	3.6	5.9	5.0
SIXTH (1980-85)	3.1	4.9	5.4
SEVENTH (1985-90)	3.1	6.2	5.9
EIGHTH (1992-97)	3.4	6.9	6.8

Source: Government of India, *Economic Survey*, 2000-2001, Tables S-4 and S-5.
Notes: GDP is estimated to be 27% industry, 25% agriculture for 2000.
   (World Bank India Data Profile: www.worldbank.org/data)

In 1991, a new industrial policy ushered in a period of truly dramatic reforms. The number of industries reserved for the public sector was halved.[6] Licensing was abolished in all but a small group of industries. Perhaps more importantly from our perspective, there were complementary changes in policies relating to trade and financial markets. Foreign investment was encouraged, quantitative import restrictions were largely abandoned and tariffs were significantly reduced. A phased reduction in import tariffs has been undertaken since. The peak tariff rate was reduced from over 300 to 110 percent in 1992, 85 percent in 1993, 65 percent in 1994, 50 percent in 1995 and 25 percent in 2003.[7]

It seems plausible that these regulatory reforms, taken together, made it much easier for firms to adopt imported technologies. We also might expect that changes in the pattern of skill demand experienced by developed countries adopting these technologies would be repeated in India in the liberalized environment of the 1990s. The ASI does display a clear pattern of skill

upgrading in the 1990s. Figure 1 shows that during the 1990s the proportion of non-manual[8]
workers in registered manufacturing increased (from 23.5 to 24.4 percent) despite the increase in
their relative wages (from 1.88 to 2.04).[9] This is in contrast to the period of declining relative
wages of non-manual workers between 1985 and 1991. Not shown is the pattern of employment
growth in registered manufacturing, which had been increasing steadily and accelerated after
1991. Since both the relative wage and the proportion of non-manual workers increased in the
1990s, it follows that the increased quantities of non-manual workers employed represent an
aggregate demand shift towards these more skilled workers.
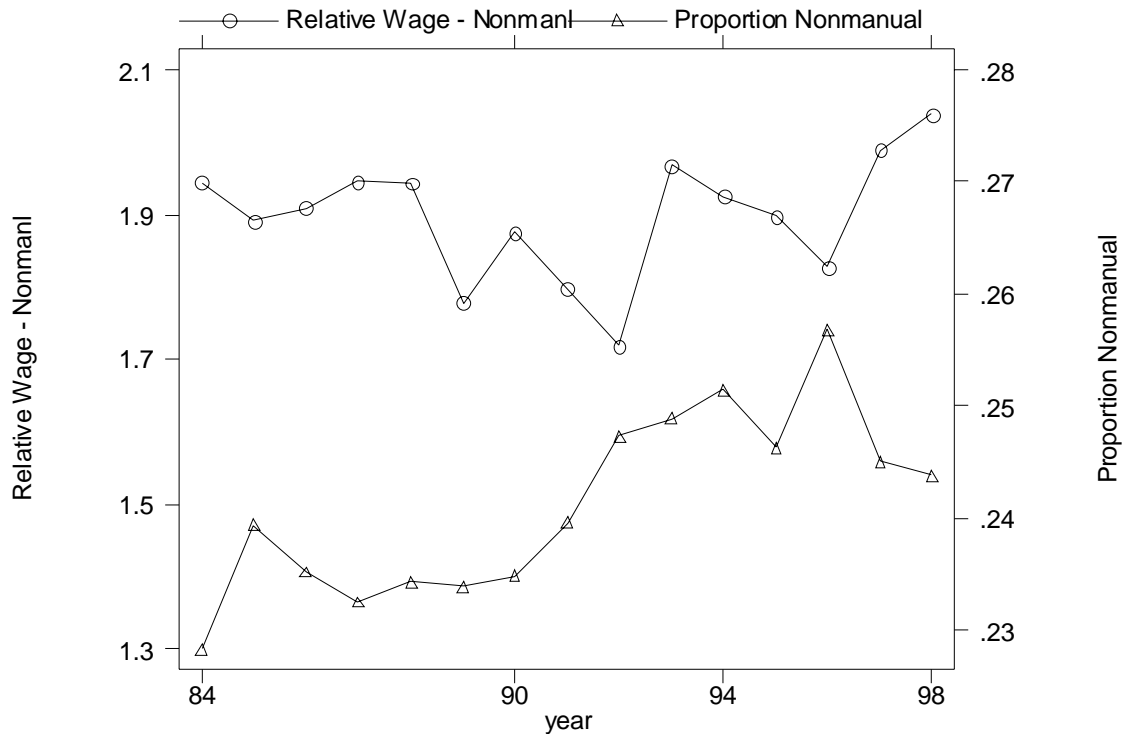

Figure 1: **Relative Wages of Non-manual (Skilled) Workers
and their Proportion in Employment - 1984-98**

During the 1985-90 period, it is hard to make a clear statement about whether demand or
supply for skills dominates. Since wages and quantities change in opposite directions one cannot
tell if shifts in demand dominate movements along a demand curve (for manual relative to non-

manual workers) in response to changes in relative wages. One way to approach that problem is to see what the diagnosis would be with an assumed aggregate elasticity of substitution. If that elasticity were unity, then the wage-bill share of non-manual workers would not be changed by supply, as changes in relative wage (in isolation) would exactly be compensated by changes in proportion employed, leaving the wage-bill constant. Any change in wage-bill share could then be attributed to relative demand shifts. As seen in Figure 2, the wage-bill share of non-manual workers declined by 0.12 percentage points per year in the 1985-91 period, indicating a reduction in demand for skills under the unitary elasticity assumption. In contrast, the wage-bill share of non-manual (i.e. skilled) workers increased in the 1990s, indicating an acceleration in demand for skills between the 1980s and the 1990s, assuming a unitary elasticity of substitution.
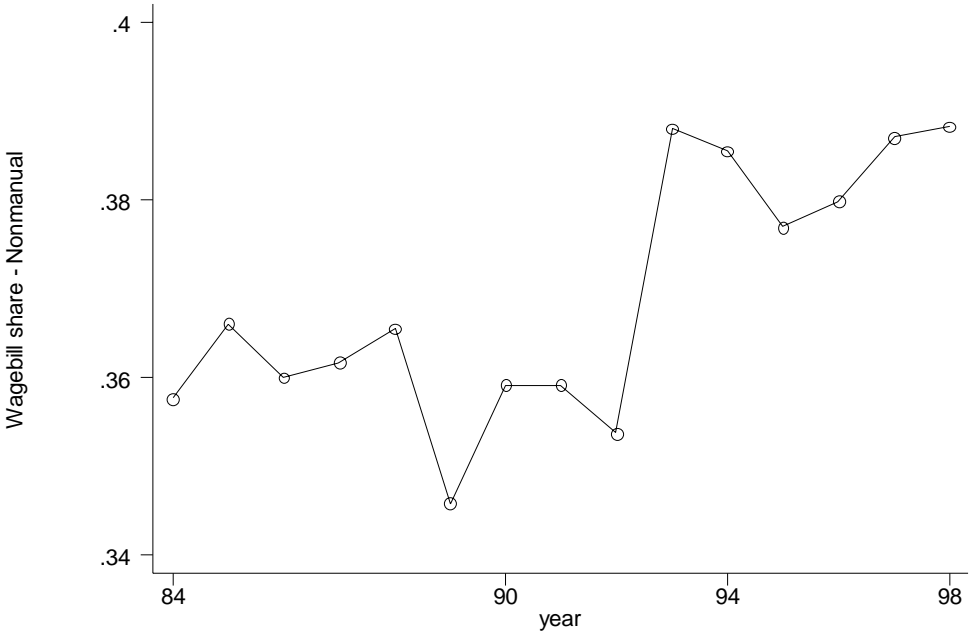

Figure 2: Non-manual (Skilled) Wage-bill Share 1984-98

Table 2: Within/Between Decompositions in High, Middle and Low Income Countries

	1970-80		1980-90		
	%ΔSn	% Within	%ΔSn	% Within	**Notes**
HIGH INCOME GROUP					
US	0.19	86	0.51	76	
Australia	**0.06**	**52**	**0.42**	**92**	**1970, 80 ,87**
Sweden	0.38	81	0.07	25	
Norway	**0.33**	**76**			**1970, 80, na**
West Germany	0.67	95	0.42	83	1970, 79, 90
Luxembourg	**0.90**	**95**	**0.73**	**123**	
Denmark	0.12	42	0.64	89	1973, 80, 89
Belgium	**0.77**	**86**	**-0.06**	**92**	**1973, 80, 85**
Finland	0.27	82	0.70	83	
Austria	**0.69**	**93**	**0.36**	**76**	**1970, 81, 90**
UK	0.39	91	0.62	92	
Japan	**0.37**	**98**	**0.14**	**98**	**1969-75, 78-90**
MIDDLE INCOME GROUP					
Venezuela	0.78	141	0.56	62	1970, 81, 91
Spain			**0.70**	**92**	**na, 80, 90**
Ireland	0.02	25	0.58	75	1970, 80, 89
Greece	**0.38**	**104**	**0.93**	**90**	
Cyprus			-0.07	108	na, 81, 91
Uruguay			**0.17**	**51**	**na, 80, 88**
Hungary			0.93	96	na, 80, 90
Portugal	**-0.97**	**96**	**0.48**	**90**	**1972, 80, 87**
Malta	-0.26	43	0.72	76	1970, 80, 88
Poland			**0.06**	**80**	**1970, 80, 89**
Chile	1.12	92	0.05	153	
Czechoslovakia	**0.06**	**61**	**0.22**	**92**	**1970, 80, 89**
Malaysia			-0.35	86	na, 83, 90
Korea			**0.08**	**36**	**1973, 80, 90**
Colombia	-0.13	145	0.66	84	1972, 80, 90
Peru	**0.13**	**-247**	**1.38**	**103**	**1972, 80, 88**
Turkey			0.60	79	na, 83, 90
Guatemala	**0.36**	**50**	**0.96**	**69**	**1973, 80, 87**
LOW INCOME GROUP					
Philippines	0.68	46			1970, 77, na
Egypt	**0.23**	**49**	**0.44**	**83**	**1971, 80, 88**
Pakistan			0.50	72	na, 80, 88
Bangladesh	**0.21**	**152**	**0.32**	**20**	**1970, 80, 88**
India	0.19	-11	-0.08	303	1970, 80, 88
Tanzania	**-0.43**	**93**	**0.65**	**84**	**1970, 80, 85**
Ethiopia			0.58	91	na, 80, 88

Note: ΔSn is the change in non-manual wage-bill share×100. The percentage "within" is the percentage of the change due to within industry increases. Data are from the United Nations General Industrial Statistics program. See Berman and Machin (2000) and Berman, Bound and Machin (1998) for data definitions and detailed descriptions of the data.

Now consider these changes in an international and historical context. Table 2 reproduces descriptive data on skill-upgrading in manufacturing industries of 37 countries in the 1970s and 1980s. Consider the share of non-production (or non-manual) workers in total wage-bill as a measure of skill use in manufacturing. The table can be summarized as follows: In a typical high income country the non-manual wage-bill share in manufacturing increased by 3-4 percentage points over the 1970s and by about 4 percentage points in the 1980s. In a typical middle income country the non-manual wage-bill share in manufacturing was stagnant in the 1970s and increased by 4-5 percentage points in the 1980s. It is hard to speak of a typical low income country since India dwarfs the other six countries in that sample. India's non-manual wage-bill share increased by 0.19 percentage points in the 1970s but *declined* by 0.08 percentage points in the 1980s. This decline was exceptional in the international context. Only three other countries in the sample of 37 experienced such a decline, and none of those were low income countries.

Our goal is to investigate the causes of that increase in demand for skills in Indian manufacturing in the 1990s. The next section describes a framework for estimation and derives an estimating equation. We then present results.

3. SKILL–BIASED TECHNOLOGICAL CHANGE – A FRAMEWORK

The first aspect of our framework is a definition of factor-biased technological change.[10] Consider a production technology

$$Y = g\,(K,\, S,\, L,\, t)\,, \qquad\qquad (1)$$

where K is capital, S is skilled labor, L is unskilled labor and t is time. Now define the bias of technological change as the rate at which the elasticity of output with respect to any factor

$$f \in (K,\, S,\, L),\ \frac{\partial \ln Y}{\partial \ln f}\,, \text{ changes with time,}$$

$$\frac{\partial^2 \ln Y}{\partial \ln f\, \partial \ln t} \equiv \gamma_f\,.$$

In this context, technological change is absolutely skill-biased if $\gamma_s > 0$. Absolute skill-bias implies increased demand for skills because their marginal product is increasing. Conversely, technological change is absolutely labor-saving if $\gamma_l < 0$, which implies decreased demand for unskilled labor. The literature has defined skill-bias as a *relative* shift in demand from unskilled to skilled workers, a definition which does not require an absolute decline in demand for unskilled workers.[11]

The skill-biased technological change (SBTC) hypothesis argues that employers' increased demand for skilled workers has been largely driven by the kinds of new technologies that are permeating modern workplaces. The critical idea is that these new technologies lead not only to higher productivity, but also favor more educated workers. As such, employers increase demand for more skilled (i.e., more educated) workers[12] who complement the new technology. At the same time, workers who do not possess the appropriate skills to operate the new technologies face decreased demand. As such, the wages and employment of the more skilled rise relative to their less skilled counterparts.

One can illustrate simultaneously rising relative wages and employment for the skilled workers in terms of a simple relative demand and supply framework, making the standard assumption that factors are paid their marginal products.
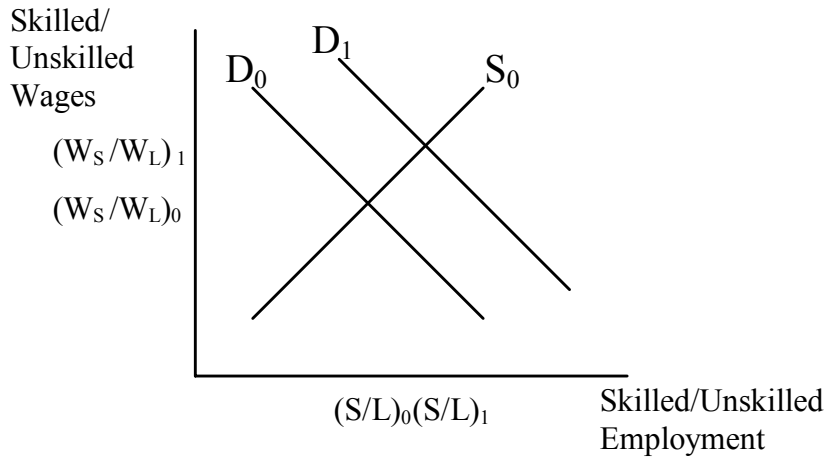
Figure 3: Supply and Demand for Skills

Figure 3 shows a labor market with two skill types, skilled and unskilled (*viz* non-manual and manual workers), where employers demand a certain number of each. Equilibrium in the model is given by the intersection of the relative demand and supply curves given by D_0 and S_0 in the Figure, with a relative wage of $(W_s/W_L)_0$ and relative employment of $(S/L)_0$.

The experience of many countries in recent years is that the ratio of skilled to unskilled wages has increased or remained steady while the ratio of skilled to unskilled employment has risen (Berman, Bound and Machin, 1998). To get such an outcome, there has to have been an outward shift in the relative demand curve. Suppose the demand curve shifts out to D_1. One then ends up with simultaneously higher relative wages and employment for the skilled at $(W_s/W_L)_1$ and $(S/L)_1$. Much of the literature has argued that the key driver of the observed relative demand shifts has been skill-biased technological change. The evidence brought to bear on this question

ranges from direct measures of technology to correlated changes across countries (see Berman and Machin (2000) for details and a summary).

The SBTC hypothesis requires that technology drives shifts in skill demand. Because of this one should see skill-use shifts occurring where employers have more to gain from the introduction of new technology. Consequently there should be systematic differences in the extent of relative demand shifts within particular workplaces, firms and industries, each of whom is likely to differ in their demand for and the extent of their use of new technologies. One test of relevance to the SBTC argument therefore comes from a decomposition of aggregate changes in skills demand (usually measured by wage bill or employment shares of skilled workers), say ΔSn, for $i = 1, \dots N$ industries as follows:

$$\Delta Sn = \sum_{i=1}^{N} \Delta Sn_i \, \bar{P}_i + \sum_{i=1}^{N} \Delta P_i \, \bar{Sn}_i \qquad (2)$$

The decomposition breaks the overall shift in skill demand into two components. The first is the within-industry component of skill upgrading (weighted by P, the relative size of industry i, where a bar is a time mean). The second measures the contribution of between-industry shifts, namely how much bigger or smaller an industry is becoming over time (weighted by the time averaged skill demand).

A number of studies using this kind of decomposition have systematically found that the bulk of the aggregate changes have occurred within, rather than between industries or workplaces. These studies cover different countries, levels of aggregation, time period and skill measures. It is clear the bulk of the skill upgrading that has occurred in OECD manufacturing since the start of the 1970s has been within, rather than between, industries.[13]

Moreover, the same is true in the developing world. Table 2 reported within-between decompositions for high, middle and low income countries. The within-industry component is

seen to be more important almost everywhere.[14] It therefore seems that across the world the within industry aspect of skill demand is what matters most. Of course that could be consistent with other possible explanations but the fact that the bulk of the shifts are seen within industries, when increased relative wages of skilled workers predict within industry skill-downgrading (i.e., substitution away from the input with the rising relative wage) provides one form of evidence. This is entirely consistent with SBTC altering relative wage and employment outcomes globally.

The evidence of the previous section is consistent with SBTC being important, but does not relate shifts in skills demand to observable technologies. Indicators of technological change such as use of computers or R&D investments have been shown to be correlated with skill-upgrading in the U.S. and U.K. (see a summary in Berman and Machin, 2000). One frequently used formal test is to estimate cost share equations relating changes in the skilled wagebill/employment share in a given industry to observable measures of technology (see Berman, Bound and Griliches, 1994). Define Sn as the wage-bill share of skilled workers. For industry *i* in year *t*, the share equation

$$\Delta Sn_{it} = \ \alpha + \beta \Delta \log(K_{it}/Y) + \gamma \Delta \log(Y_{it}) + \delta \Delta \log(w_S/w_L)_{it} \qquad (3)$$

can be derived from a translog cost function dual to the production function in (1) with two labor inputs (skilled and unskilled), assuming capital to be a quasi-fixed factor. Constant returns to scale imply $\gamma = 0$, though γ may also capture short term cyclical fluctuations likely in Sn (perhaps due to differential adjustment costs in hiring and releasing skilled and unskilled workers).

Capital skill complementarity (Griliches, 1969) implies $\beta > 0$. One possible explanation for increased demand for skill is capital-skill complementarity combined with an increased capital-output ratio. While capital-skill complementarity is important in explaining the cross-sectional pattern of skill use in U.S. manufacturing, it turns out to be a relatively minor source of

13

skill upgrading in the past few decades (Berman, Bound and Griliches, 1994). Nevertheless, *changes* in capital skill complementarity will reflect changes in skill-bias of technology embedded in capital. We investigate both the level and change in β in estimates below.

The share equation approach can be expanded to allow us to test the effects of imports (I) and exports (X). In an economy abundant in unskilled labor increased exports or imports will induce a shift towards production of goods intensive in unskilled labor.[15] To the extent that this shift occurs within industries (which we measure in 3 digit industry aggregates) we expect that the coefficients on imports and exports (φ and η) will be negative in the following equation.

$$\Delta Sn_{it} = \alpha + \beta\Delta\log(K/Y)_{it} + \gamma\Delta\log(Y_{it}) + \delta \Delta\log (w_S/w_L)_{it}$$

$$+ \phi\Delta\log(I/Y)_{it} + \eta\Delta\log(X/Y)_{it} \qquad (4)$$

In the literature this equation often includes an indicator of technological change, such as R&D, investment in computers or significant innovations. Those data are lacking in the ASI.

Turning to estimation issues, the presence of the relative wage on the right hand side when the wage-bill share is on the left opens up the possibility of endogeneity bias or of spurious correlation due to measurement error in wages, which may be reflected in the wage-bill share. For that reason we choose to drop the relative wage term from the estimated equation and risk an omitted variable bias. If labor markets clear sufficiently so that relative wages undergo the same changes across industries, that omitted term will be absorbed in the constant. Alternatively a unitary elasticity of substitution between skilled and unskilled workers implies δ=0. We thus arrive at an estimating equation:

$$\Delta Sn_{it} = \alpha + \beta\Delta\log(K/Y)_{it} + \gamma\Delta\log(Y_{it}) + \phi\Delta\log(I/Y)_{it} + \eta\Delta\log(X/Y)_{it} + \varepsilon_{it} \qquad (5)$$

We turn in the next section to a discussion of the data used to test the SBTC hypothesis for Indian manufacturing, followed by the results.

4. DATA AND RESULTS

The analysis is based on the India Annual Survey of Industry (ASI) which was available to us from 1983/84 through 1997/98 disaggregated by state and 3 digit (NIC) industry.[16] This is a survey of registered manufacturing firms, reporting employment in two skill categories (non-manual and manual workers), which we interpret as representing skilled and unskilled labor, respectively. The data also contain wage-bills for each labor category, output, value added, capital stock and a number of other variables.[17]

The public-use ASI data are of uneven quality. We discovered numerous internal and external inconsistencies in these data and believe that we have resolved most of them. In keeping with the Griliches' tradition of attention to measurement issues (Griliches, 1986) we discuss what we've learned here. (A separate appendix on data construction is available upon request.) We examined time-series of employment for sudden changes in each 3 digit industry by state, and then compared these figures with totals available from the Central Statistical Organization with data from other sources when any inconsistencies remained unexplained. We found two types of data problems:

1) Possible coding mistakes - The data indicate a very sharp decline in employment in West Bengal between 1984 and 1985, from 1.1 million manufacturing workers to 800 thousand. 180 thousand of that decline is reported in one 3 digit industry, aluminum manufacturing (NIC 335)[18]. Similar declines are reported for value added, output and other statistics. That sharp reduction in employment is inconsistent with the slight but steady employment *increase* reported in official statistics by the Bureau of Economics and Statistics in the Government of West Bengal.[19] Compared to national totals for employment, the 1984 figures from our ASI data seem to be about 160,000 too high, indicating that this one industry is probably the source of the entire

mistake. Recognizing this, our analysis is conducted both with and without the suspect West Bengal data. Happily, the focus of our analysis – the wage-bill share of non-manual workers – is not particularly sensitive to the treatment of West Bengal in 1984.

2) Inconsistent aggregation - We found that at the 4 digit industry level a large number of industry-state observations were present in some years but missing in previous or subsequent years, apparently due to a policy of aggregating observations across industry classifications in order to preserve confidentiality. This policy is described in ASI documentation. Unfortunately, this aggregation is not performed consistently over time, so that industries seem to pop in and out of the data. Our solution to this problem was to deal with industries at the 3 digit level of aggregation in (state x industry) analysis and to restrict our attention to States in which employment was large enough to avoid confidentiality problems at the three digit level. Previous work on U.S. manufacturing has not been sensitive to this type of aggregation.

Results

Table 3 reports changes in relative wages and quantities for non-manual and manual workers for the pre- and post-reform sample periods, 1984-89 and 1990-98 respectively. Recall that non-manual workers are the higher education, or "skilled" category. During the 1990-98 period, the proportion of non-manual workers in employment increased by 0.10 percentage points per year, while their relative wages increased by 1.07 percent annually. In contrast, during the 1984-89 period the employment share of non-manual workers dropped by 0.23 percentage points annually, while their relative wages increased at a rate of 0.26 percent per year.

The aggregate increase in demand for non-manual workers in the 1990s is evident in the fact that their proportion and relative wage increased at the same time. What accounted for this demand shift?   Skill-bias in technological change is one possibility, but not the only one. A shift

in the composition of output due to trade, shifts in tastes or scale effects could all cause demand

for non-manual workers to increase as skill-intensive industries increase their employment shares.

As a first step in diagnosis we decompose changes in the proportion of skilled labor in

employment into *within-* and *between-* industry components as outlined above. Within-industry

shifts in the wage-bill indicate a shift in demand within industries. Those could be due to SBTC

or capital-skill complementarity (which we analyze below), but cannot be due to shifts in the

industrial distribution of employment or wagebill.

Table 3: Within Industry Changes in Employment of Skilled Labor:
Annualized Changes

	84-89	90-98
Δ employment share (x100)	-0.23	0.10
% within	**128.05**	**85.14**
Δ wagebill share (x100)	-0.23	0.37
% within	**175.31**	**89.45**
% Δ in relative wage (w_n / w_p)	0.26	1.07

Note: percentage "within" is the percentage of the change due to within industry increases,
according to the decomposition discussed in the text. The percentage change in the relative wage
of non-manual workers is also an annual average.

The key point of Table 3 is that during the 1990s these "within" industry proportions are

positive and the dominant term in Indian manufacturing. A full 85 percent of the increase in

employment share and 89 percent of the increase in wage-bill share of skill occur *within* two digit

industries. That indicates industries were substituting *toward* the employment of skilled labor

despite the rising relative wage of skill. In this sense India in the 1990s reproduces the pattern

17

familiar from our other studies in the 1980s in the manufacturing sectors of the vast majority of countries surveyed, as reported in Table 2.

In diagnosing changes in demand for skills, shifts in supply are a confounding factor. One approach to neutralizing the effects of supply shifts is to assume an elasticity of substitution of unity between skilled and unskilled labor, so that the wage-bill is invariant to movement along the relative demand curve as in Figure 3 above. That approach recommends the wage-bill share of non-manual workers as a measure of demand for skills, since it shifts only with demand under the assumption. Figure 2 illustrates that approach for the ASI data. The non-manual share of wage-bill drops between 1984 and 89 and then rises fairly steadily through the 1990s. Compared to the two series in Figure 1, relative wages and proportion of non-manual workers in employment, the wage-bill share series is smoother, suggesting that indeed supply shifts are being muted in this series by motion along a demand curve.

India is a country of diverse manufacturing technologies spread across vast distances with poor transport between States and between interior States and foreign markets. Consequently, one might suspect that shifts in demand for skill would differ across States. Table 4 investigates cross-state differences in demand for skills in manufacturing, reporting for each state in both periods the change in wage-bill shares of non-manual workers, the proportion of that change that occurs within industries and the change in relative wages. Note that registered manufacturing employment varies widely across states (as does population) from a high of 1.5 million in Maharashtra to just 11 thousand in Chandigarh. Six states are not reported as they have so little employment that reclassification across 3 digit industries (NIC) may be suspect.

Table 4 reports three clear findings about demand for skills in the 1990s. First, in fully 19 of the 21 States the wage-bill share of non-manual workers increased in the post-reform sample

period between 1991 and 1998. The only exception among the large states was West Bengal. Second, in 10 of those 14 cases the proportion of that change which occurred within industries was strongly positive (over 60 percent), providing a preliminary indication of SBTC. Third, despite the similar sign of these changes, the size varied considerably across regions. This last finding—of diversity in skill upgrading—mimics the popular perception of widely different growth in manufacturing across regions.

Table 4: Changes in Wage-bill Shares by State and Period

State[*]	84-89			90-98			1998 Employment (1000s)
	Δ Sn	% within	% Δ w_n/w_p	ΔSn	% within	% Δ w_n/w_p	
Andhra Pradesh	-0.91	125.62	-8.49	0.43	45.34	0.90	985
Assam	0.05	55.81	0.70	-0.33	111.58	-1.43	132
Bihar	-0.80	116.90	-2.33	0.26	143.20	-0.49	262
Chandigarh	-0.37	-25.32	-2.96	0.82	124.42	-0.20	11
Delhi	0.33	-51.82	-2.14	0.64	116.21	1.80	128
Goa, Daman and Diu	-0.94	69.80	-2.66	--	--	--	45
Gujarat	0.39	-60.98	-1.72	0.89	51.34	1.80	825
Haryana	-0.61	109.84	-5.22	0.82	67.60	1.91	277
Himachal Paradesh	-0.90	80.16	-0.77	0.85	55.57	2.54	38
Jammu and Kashmir	1.18	56.87	0.22	-0.02	-672.83	0.76	24
Karnataka	0.16	-120.96	-1.60	0.52	120.53	3.61	582
Kerala	0.18	18.22	-2.44	0.03	91.35	-3.67	360
Madhya Paradse	0.20	-8.72	0.82	-0.11	182.23	-1.02	380
Maharashtra	-0.43	144.10	-1.49	0.53	94.38	2.57	1,423
Orissa	0.06	-230.79	3.76	-1.44	99.53	-4.26	142
Punjab	-0.33	139.48	5.25	0.88	96.58	2.42	332
Pandicherry	0.89	-33.03	3.84	1.22	27.13	7.22	35
Rajasthan	0.84	72.33	0.91	0.13	-67.10	-0.31	242
Tamil Nadu	-0.44	78.40	-1.56	0.14	170.83	0.53	1,203
Uttar Pradesh	0.37	-0.78	-0.59	0.30	87.35	0.25	674
West Bengal	-0.55	83.01	15.68	-0.07	-109.40	0.86	760
Total	-0.23	175.31	0.26	0.37	89.45	1.07	8,900

Notes: **1.** ΔSn is the change in non-manual wage-bill share $\times$ 100. The percentage "within" is the percentage of the change due to within industry increases, according to the decomposition discussed in the text. The percentage change in the relative wage of non-manual workers is also an annual average.
2. The table omits six state groupings with less than 10,000 employed persons in manufacturing: Dadar, Nagar and Haveli, Tripura, A&N Islands, Meghalaya, Nagaland and Manipur.

To estimate equation (5), the share equation, we divided the ASI data into two sub-periods, from 1984 through 1989 and from 1990 through 1998. (We exclude the 1989-90 transition because of inconsistencies in the redefinition of industries, as noted above).

Table 5: Descriptive Statistics - Manufacturing Industries 1984-98

	Annualized Change 1984-89		Annualized Change 1990-98	
	Mean	Std. Dev	Mean	Std. Dev.
Non-manual share in wage-bill	-0.0041	0.0062	0.0031	0.0036
Log capital	0.059	0.084	0.131	0.052
Log value added	0.043	0.074	0.104	0.045
Log imports	0.112	0.146	0.126	0.113
Log exports	0.139	0.144	0.115	0.092

Note: Annualized changes for 76 four-digit (ISIC) manufacturing industries for all of India in each period.

Table 5 reports summary statistics. Recall that the 1984-89 period largely preceded economic reforms, and was characterized by a decreased proportion of non-manual (skilled) workers by 0.41 percentage points per year. In contrast, in 1990-98 the proportion of non-manual workers increased by 0.31 percentage points per year.[20] Note that imports and exports also grew rapidly in both periods, but the 1990s stand out in the rapid growth of investment and value added. For instance, capital grew by over 13.1 percent per year and value added by 10.4 percent so that the capital/value added ratio increased by 2.7 percent annually.

The share equations derived demonstrate the relative importance of output growth, capital, imports and exports in demand for skills. Table 6 reports the result of estimating equation (5) using the national data for 76 "4 digit" (ISIC)[21] industries. The left four columns of results report separate estimates for each period, revealing the contrast between periods. In 1984-89 growth in

the K/Y explains little of the decline in the wage-bill share of non-manual workers, with a small and statistically insignificant coefficient. In contrast in 1990-98 the coefficient on growth in K/Y is large and statistically significant, at 0.0263. This larger coefficient in the 1990s indicates that capital-skill complementarity increased between the 1980s and 1990s. That increase in capital-skill complementarity, coupled with the growing K/Y ratio in the 1990s, may explain some fraction of the increased demand for skills in manufacturing during the 1990s.

Table 6: Estimated Wage-bill Share Equations - National Manufacturing 1984-98
Estimates for 76 four digit industries at the National Level

Dep. variable: Change in non-manual wagebill share	1984-89		1990-98		Pooled 1984-89 / 1990-98			
1990s indicator					**0.0071** (.0010)	**0.0067** (.0010)	**0.0036** (.0014)	**0.0033** (.0016)
d Log capital/value added	0.0022 (.0156)	0.0010 (.0150)	**0.0263** (.0104)	**0.0279** (.0103)		0.0007 (.0147)	0.0022 (.0157)	0.0011 (.0149)
d Log capital/value added x 1990s						0.0157 (.0179)	0.0240 (.0188)	0.0281 (.0184)
d Log value added	0.0050 (.0116)	0.0065 (.0123)	**0.0297** (.0100)	**0.0317** (.0114)			0.0050 (.0117)	-0.0043 (.0147)
d Log value added x 1990s							0.0247 (.0153)	0.0254 (.0165)
d Log imports/value added		-0.0065 (.0067)		-0.0033 (.0030)				-0.0055 (.0045)
d Log exports/value added		-0.0054 (.0088)		-0.0041 (.0046)				-0.0054 (.0065)
Constant	-0.0043 (.0009)	-0.0029 (.0015)	-0.0007 (.0011)	-0.0001 (.0015)	-0.0041 (.0008)	-.0041 (.0008)	-.0043 (.0009)	-0.0030 (.0013)
R^2	0.00	0.05	0.16	0.17	0.33	0.34	0.36	0.38
Observations	76	76	76	76	152	152	152	152

Note: Figures are annualized changes for 76 four-digit (ISIC) manufacturing industries for all of India in each period. Heteroskedasticity-consistent standard errors are reported in parentheses. Regressions estimated by weighted least squares with wage-bill shares averaged over the period as weights. Coefficients are significant at the 5% level in bold face. See equation (4) in text.

The other variables in this specification are also interesting. The coefficient on value added indicates that faster growing industries also increased their wage-bill share of non-manual workers, in violation of the constant-returns hypothesis, which implies that input shares are invariant to scale.

Imports and exports have negative coefficients in this regression, consistent with a Heckscher-Ohlin approach to our industry regressions, suggesting that exports and imports reduce skill content within industries in an unskilled labor abundant country by reallocating production to less skill-intensive products. (This is the opposite of increasing skill-content, which would be the case if India traded primarily with a less skill-abundant country or exported mainly goods which were skill-abundant for India.) These coefficients are small and statistically insignificant but nevertheless explain some reduced demand for non-manual workers, especially in the 1980s.

The four rightmost columns of Table 6 examine how much of the acceleration in the wage-bill share of non-manual workers can be attributed to covariates, mostly output growth and capital-skill complementarity. Using the pooled sample, the coefficient on the constant is the annualized change in the non-manual wage-bill share between 1984 and 1989, which is negative 0.0041 in the baseline specification (as in Table 5). The coefficient on the indicator for the 1990s, 0.0071, reflects the acceleration in the non-manual wage-bill share from -0.0041 to +0.0031 (with a little rounding error). Adding covariates as we move to the right explains about half that acceleration, reducing the coefficient to 0.0033 in the rightmost column. Specifically, including the change in log K/Y and the change in log Y explain about half the acceleration between them, if those coefficients are allowed to differ between the 1980s and 1990s. Yet, the specification with only the capital skill complementarity term (the 6th column) has a coefficient

22

on the 1990s of 0.0067, indicating that the change in capital-skill complementarity alone explains very little of the acceleration (1 - .0067/.0071 = 6 percent).

Table 7: Estimated Wage-bill Share Equations -State Manufacturing 1984-98
Pooled sample of three digit industries for 22 states.

Dep. variable: Change in non-manual wage-bill share	1984-89	1990-98	Pooled 1984-89 / 1990-98				
1990s indicator			**0.0073** (.0010)	**0.0066** (.0013)	**0.0038** (.0014)	**0.0044** (.0013)	**0.0043** (.0015)
d Log capital/value added	0.0024 (.0079)	**0.0343** (.0067)		**0.0132** (.0060)	0.0024 (.0079)	0.0018 (.0079)	0.0045 (.0072)
d Log capital/value added x 1990s					**0.0320** (.0104)	**0.0278** (.0104)	**0.0250** (.0101)
d Log value added	-0.0001 (.0088)	**0.0283** (.0084)		0.0111 (.0065)	-0.0001 (.0088)	-0.0002 (.0081)	0.0044 (.0081)
d Log value added x 1990s					**0.0284** (.0121)	**0.0219** (.0104)	**0.0240** (.0120)
Constant	**-0.0043** (.0009)	-0.0005 (.0011)	**-0.0042** (.0008)	**-0.0048** (.0009)	**-0.0043** (.0009)	**-0.0042** (.0008)	**-0.0046** (.0008)
State effects						X	
Industry effects							X
R²	0.001	0.10	0.14	0.15	0.17	0.21	0.24
Observations	453	495	948	948	948	948	948

Note: Figures are annualized changes for 3-digit manufacturing (ISIC) industries in twenty one state groups. Heteroskedasticity-consistent standard errors are reported in parentheses. Coefficients significant at the 5% level are in bold face. Regressions estimated by weighted least squares with wage-bill shares averaged over the period as weights. See equation (4) in text.

Table 7 reports sharper estimates using the richer dataset available by using variation across both states and industries. The results are qualitatively the same as those in Table 6: capital-skill complementarity is much stronger in the 1990s after the reforms, the coefficient increasing by an order of magnitude, from 0.0024 to 0.0343. The two rightmost columns report

that this increase in the capital-skill complementarity coefficient (0.0320 or 0.0278, depending on specification) is large and statistically significant. As in Table 6 very little of the acceleration in skill upgrading is explained by capital-skill complementarity – the inclusion of a K/Y term which varies over time reduces the coefficient on the 1990s only slightly, from 0.0073 to 0.0068.

Tests of Robustness

We carried out a number of robustness checks on these share equation estimates. Sensitive to the idea that states may have very different experiences, one test is to run the same regression allowing each state a secular trend in the non-manual wage-bill share, perhaps to allow for local changes in trade, infrastructure investment, regulation, business cycles or technological change. Allowing for state fixed effects in growth hardly changes the estimated coefficients, as shown in the rightmost column of Table 7. The 1990s increase in the capital-skill complementarity and output coefficients is reduced only slightly by allowing for state effects. Surprisingly, allowing states a separate trend in changing wage-bill shares of non-manual workers increases the R^2 by only four percentage points.

Table 8 reports tests of robustness to alternative sampling methods. Recall that we split the sample in an unusual way to avoid the 1989-90 industry recoding and that we had some doubts about observations in the early period from West Bengal. Table 8 reports estimated share equations using two different definitions of the periods and excluding West Bengal. We try three approaches: a) redefining the periods as 1984-90 and 1990-98, spanning the industry recoding of 1989-90; b) redefining the periods as 1984-91 and 1991-98 to reflect the pre- and post-reform periods; and c) omitting West Bengal data altogether and using the period definitions 1984-89 and 1990-98 as in the previous tables. Increased capital-skill complementarity is evident in all

these estimates and is statistically significant in 5 of the 6 specifications. As such, the finding of increased capital-skill complementarity in the 1990s is robust to different redefinitions of the sample.

Table 8: Robustness Tests

Dependent variable: Change in non-manual wage-bill share	National Level			State Level		
	84-90 90-98	84-91 91-98	84-89 90-98 without WB	84-90 90-98	84-91 91-98	84-89 90-98 without WB
1990s indicator	0.0009 (.0016)	0.0017 (.0017)	**0.0032** (.0015)	0.0015 (.0015)	0.0014 (.0013)	**0.0036** (.0016)
d Log capital/value added	-0.0212 (.0173)	0.0035 (.0149)	-0.0067 (.0157)	-0.0153 (.0091)	-0.0088 (.0079)	0.0015 (.0087)
d Log capital/value added x 1990s	**0.0475** (.0202)	0.0192 (.0185)	**0.0400** (.0198)	**0.0496** (.0113)	**0.0327** (.0097)	**0.0331** (.0112)
d Log value added	-0.0098 (.0139)	-0.0182 (.0122)	0.0056 (.0117)	-0.0017 (.0095)	**-0.0165** (.0068)	-0.0003 (.0090)
d Log value added x 1990s	**0.0395** (.0171)	**0.0457** (.0161)	0.0267 (.0155)	**0.0300** (.0127)	**0.0484** (.0097)	**0.0297** (.0126)
Constant	-0.0016 (.0010)	-0.0014 (.0009)	**-0.0042** (.0010)	**-0.0020** (.0009)	-0.0014 (.0008)	**-0.0041** (.0010)
R^2	0.21	0.31	0.36	0.12	0.17	0.17
Observations	152	156	151	947	949	896

Note: Annualized changes for 76 four-digit manufacturing industries for all of India in each period in columns 1-3 and for three-digit manufacturing industries in twenty two state groups in columns 4-6. Heteroskedasticity-consistent standard errors in parentheses. Estimated by weighted least squares with wage-bill shares averaged over the period as weights. Coefficients significant at the 5% level in bold face. See equation (4) in text.

These different robustness tests together argue strongly for a clear conclusion: Increased demand for non-manual workers in Indian manufacturing in the 1990s can be largely attributed to the combination of three factors: increased capital-skill complementarity, increased investment

and increased output. The first two are consistent with the idea of skill-biased technological change embodied in new investment yet they account for only a small fraction of the acceleration in skill-upgrading between the 1980s and 1990s. The increase in output alone predicts almost half of that acceleration, which is really a surprise. Fast growing industries are upgrading their skill mix faster than slow-growing or stable industries.

To put the estimated capital-skill complementarity coefficients in context, compare them with U.S. estimates. For U.S. manufacturing the comparable capital-skill complementarity coefficient (estimated in a similar regression) in 1959-86 is 0.038 (see Berman, Bound and Griliches, 1994), and for the 1979-86 period is 0.064. Thus, these estimates indicate that capital-skill complementarity in Indian manufacturing increased from an estimated zero in the 1980s to a level in the 1990s comparable to the U.S. level for the 1960s and 1970s. We interpret this as evidence of skill-biased technological change for technology embodied in *new* capital.

Is increased capital-skill complementarity in Indian manufacturing related to the pattern of skill-biased technological change evident in the manufacturing sectors of OECD and middle income countries? One way to look at this is to ask whether the same industries upgrade skills in different countries at the same time. This cross-country correlation approach has shown consistent patterns of skill upgrading in many industries across countries in the OECD in the 1980s (Berman, Bound and Machin, 1998). Those same industries generally underwent skill-upgrading in middle-income countries in the 1980s as well (Berman and Machin, 2000).

Table 9 reports the result of a similar exercise for our Indian data, in which we ask if skill upgrading in Indian industries in the 1990s is predicted by upgrading in the same industries in previous decades in the U.S., after accounting for the effects of capital-skill complementarity and increased output.

Table 9: Estimated Wage-bill Share Equations allowing Cross-Country Correlations
State Manufacturing 1990-98 using three digit industries for 22 states.

Dep. variable: Change in non-manual wagebill share	1990-98				
d Log capital/value added	**0.0343**	**0.0343**	**0.0339**	**0.0338**	**0.0342**
	(.0067)	(.0067)	(.0067)	(.0068)	(.0066)
d Log value added	**0.0285**	**0.0284**	**0.0282**	**0.0281**	**0.0285**
	(.0084)	(.0084)	(.0084)	(.0085)	(.0083)
d non-manual wage-bill share for US in 1960s	0.130				
	(.243)				
d non-manual wage-bill share for US in 1970s		0.104			
		(.208)			
d non-manual wage-bill share for US in 1980s			-0.097		
			(.256)		
d non-manual wagebill share for middle income in 1970s				-0.006	
				(.015)	
d non-manual wagebill share for middle income in 1980s					0.015
					(.011)
Constant	0.0007	-0.0007	-0.0002	-0.0003	-0.0002
	(.0011)	(.0011)	(.0014)	(.0012)	(.0014)
R^2	0.10	0.10	0.10	0.10	0.11
Observations	495	495	495	495	495

Note: Figures are annualized changes for three-digit manufacturing industries in twenty two state groups. Heteroskedasticity-consistent standard errors reported in parentheses. Coefficients significant at the 5% level are in bold face. Regressions estimated by weighted least squares with wage-bill shares averaged over the period as weights. See equation (4) in text.

The answer is negative. There is only weak evidence of a correlation with U.S. skill upgrading in the same industries in the 1960s and 1970s and a weak negative correlation with the U.S. pattern in the 1980s. Interestingly enough, the Indian pattern of skill upgrading in the 1990s is also not strikingly similar to that in middle-income countries either, showing a weak positive

correlation with the middle-income pattern for the 1980s and a negative correlation with the middle income pattern of skill-upgrading for the 1970s. Thus, in contrast to middle-income countries, India's participation in an international pattern of skill-biased technological change seems to be limited to technologies embodied in capital or somehow related to increased output.

Table 10: Estimated Wage-bill Share Equations – State and Industry Effects
State Manufacturing 1990-98 using three digit industries for 22 states.

Dependent variable: Change in non-manual wage-bill share	1990-98		
d Log capital/value added	**0.0343**	**0.0328**	**0.0324**
	(.0067)	(.0078)	(.0067)
d Log value added	**0.0283**	**0.0268**	**0.0184**
	(.0084)	(.0092)	(.0069)
Constant	-0.0005	-0.0003	0.0006
	(.0011)	(.0012)	(.0009)
28 industry effects		X	
20 state effects			X
R^2	0.10	0.16	0.27
Observations	495	495	495

Note: Figures are annualized changes for three-digit manufacturing industries in twenty two state groups. Heteroskedasticity-consistent standard errors are reported in parentheses. Coefficients significant at the 5% level are in bold face. Regressions estimated by weighted least squares with wage-bill shares averaged over the period as weights. See equation (4) in text.

One remarkable feature of skill-upgrading in India is the different experiences across states in the 1990s. Even among the states with large manufacturing sectors, the growth in wage-bill share of skilled workers ranges from a high of 0.89 percentage points a year in Gujarat to a low of –0.07 percentage points per year in West Bengal (as reported in Table 4). Table 10 reports that this heterogeneity in skill upgrading across states remains evident when covariates are

included in estimating the share equation. While including state effects in the regression has little effect on the estimated coefficients it does increase the R^2 quite a bit, from 0.10 to 0.27. This is interesting in the context of recent work which relates productivity growth in the post-liberalization period to state-level regulations (Aghion et al., 2003). We tried replicating those results by checking if changes in state-level labor regulations in the late 1980s predicted skill upgrading in the 1990s using measures from Besley and Burgess (2002).[22] The answer is negative. Skill-upgrading in India was not restricted to a few states which followed particular policies. It appears to be a more a general phenomenon.

In unreported results we have attempted to investigate the effects of one state-specific factor: electricity generated within the state. That variable also has no explanatory power. Further exploration of skill-upgrading in India may do well to focus on state-specific factors such as differences in infrastructure investment and regulation,[23] and in employment protection legislation in the 1990s.[24]

5. Conclusions

Indian manufacturing was unusual in the 1980s in the falling proportion of non-manual (relatively skilled) workers in employment, bucking a worldwide trend which has been associated with skill-biased technological change. The 1990s were different, though. The proportion of non-manual workers in employment increased, as did the non-manual share of the wage-bill. All this took place against the backdrop of various economic reforms instituted in the early 1990s, and acceleration of investment and productivity.

Is the increased use of skilled workers in Indian manufacturing in the 1990s due to SBTC? The answer is uncertain. On the one hand, most of the skill upgrading occurred *within* 4 digit

industries (using the ISI classification), indicating that it was largely ***not*** due to shifts from low to high skill industries as would be the case if trade patterns or preferences for goods had changed. Furthermore, estimated capital-skill complementarity increased significantly between the 1980s and 1990s from about zero, to a level similar to that for U.S. manufacturing in the 1960s or 1970s. This could well be due to skill-biased change in technologies embodied in capital.

On the other hand, the combination of increased capital-skill complementarity and increased investment account for very little of measured skill-upgrading, assuming constant returns to scale. The only variable that consistently predicts skill upgrading in Indian industries is increased output. Why growing output predicts skill upgrading is a mystery for future research. We can speculate, though. One possibility is that restrictions on layoffs reduce the ability of firms to adjust their skill mix to make it appropriate for new technologies. Rapidly growing firms can raise the proportion of skilled workers by hiring them disproportionately while firms with stable employment may not do so. That constrained labor demand explanation is consistent with the pattern shown by U.S. manufacturing in the recession of the early 1980s, when firms freed of the usual firing constraints by the crisis laid off less-skilled workers disproportionately while new hires in the recovery were on average more skilled.

Another reason to doubt that SBTC is a major influence is that the industries undergoing skill-upgrading are not the typical suspects revealed by cross country correlations in the literature. Data on investments in technology would help us understand why demand for skills has increased in some industries and not in others. This would be a particularly interesting investigation in India as tariffs on computers were reduced sharply in the early 1990s.

An important topic for future research is the high cross-state variation in increased demand for skills in registered manufacturing. Among the states with large manufacturing

sectors, the rapid increase in demand for skills in Haryana, Karnataka and Punjab in particular is not well explained by their industrial composition, capital-skill complementarity or the increased output effect.

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[2] University of California San Diego and National Bureau of Economic Research; University of Michigan and Indian Statistical Institute; and Lead Economist, World Bank Institute, respectively.

[3] Pavcnik (2002) finds that in Chile adoption of foreign technology is associated with higher levels of skilled labor in the wagebill, but that in first differences those associations are statistically insignificant. Attanasio et al (2004) use Columbian micro data, finding that the increase in skill demand was ubiquitous but larger in sectors with big tariff reductions.

[4] A description of these policies can be found in the relevant volumes of the Handbook of Industrial Policy and Statistics and the Economic Survey, both annual government publications.

[5] Economic Survey , 1985-6, chapter 4.

[6] The number of industries reserved for the public sector went down from 17 in 1956 to 8 in 1991 (Economic Survey, 1991-2).

[7] The rates up until 1995 are from the Economic Survey, 1995-6, p31. The current rate is from the Budget Speech of the Finance Minister, February 28, 2003.

[8] We refer to manual workers as unskilled and non-manual workers as skilled, following the standard practice in this literature. Nonmanual workers generally have higher wages and work in occupations requiring more education. See Berman-Bound and Machin (1998) and Berman and Machin (2000) for more discussion.

[9] These figures exclude West Bengal because of an apparent measurement problem in 1984 (see text in Section 4 for details).

[10] See Berman (2000) for a more detailed derivation.

[11] Technically, it is equivalent to $\dfrac{\partial \ln Y}{\partial \ln S}$ growing at a faster rate than $\dfrac{\partial \ln Y}{\partial \ln L}$, or in the Cobb-Douglas case to the exponent of S growing at a faster rate than the exponent of L.

[12] We follow the standard practice in this literature of using the term "skill" to loosely refer to human capital accumulated through education. A craftsman with low education in manufacturing would be an "unskilled" worker in this analysis.

[13] For example, Berman and Machin (2000) provide a summary of studies from the US and UK.

[14] Sanchez-Paramo and Schady (2002) confirm the same finding for six Latin American countries (Argentina, Bolivia, Brazil, Chile, Colombia and Mexico).

[15] For studies on the links between trade liberalization and relative wages, see Lawrence and Slaughter (1993), Robbins (1995), and Hanson and Harrison (1995).

[16] NIC is the National Industrial Classification used in India.

[17] We adjusted the pre-1990 data (based on NIC-70) to reflect the adoption in 1990 of a new industrial classification system (NIC-87). This involved developing and applying a cross-walk between NIC-70 and NIC-87 to accommodate the industries that were either merged, split up, or mixed (both merged and split).The NIC70-NIC87 cross-walk is available upon request from the authors.

[18] NIC code 335 corresponds to ISIC code 3720, which is classified as non-ferrous metal basic industries.

[19] Sources: Table 4.2 in Statistical Appendix to Economic Review 1990-91 of Government of West Bengal. The Table in turn cites the following: National Employment Service, West Bengal, and Bureau of Applied Economics, Bengal; Table 11.5 in West Bengal Statistical Handbook 1997 of Bureau of Applied Economics and Statistics, Government of West Bengal. The Table itself uses as source the Directorate of Cottage and Small Scale Industries, West Bengal; Chief Inspector of Factories, West Bengal. We thank Professor Dilip Mookherjee of Boston University for generously pursuing this investigation.

[20] These figures differ slightly from those in Table 2 as we have restricted the sample to observations in which all the covariates are present.

[21] Three-digit NIC translates into four-digit ISIC.

[22] We thank a referee for suggesting this to us.

[23] The Investment Climate, varying across Indian states, may also be a contributing factor for these differences

[24] For example, see Besley and Burgess (2002) on the role of cross-state differences in employment protection legislation on variations in economic growth across states in India.