Effects of Trade liberalisation, Environmental and Labour Regulations on Employment in India's Organised Textile Sector

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Abstract

In recent years, employment has fallen in the organised textile sector despite an aggregate rise in output and capital. This paper analyses the role of various factors that influence employment using 3-digit classification of Indian textile industry from 1973-74 to 1997-98. Our results document that the fall in employment can be explained in terms of rise in wages, output shocks, lack of capital utilisation and trade restrictiveness pertaining to Multi Fibre Arrangement (MFA). Environmental regulations enhance employment in the sub-sectors that are most likely to be influenced by them. The results are robust to different measures of capital, its utilisation and disaggregation to state-level. We also illustrate that in a post-MFA regime, employment in the sector is bound to increase owing to absence of trade restrictions and prospects of huge investment in general and in complying with environmental regulations, though the labour regulations might affect the magnitude of that increase.

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1 Introduction

The Indian textile and clothing sector is the second largest employer in India after agriculture, with more than 35 million persons engaged in it. It contributes 5% to the Gross Domestic Product (GDP) of the country, 30% to the total exports of India and 20% to our industrial production. By virtue of being among the earliest established industries in the country and being the key sector responsible for rapid growth of the newly industrialised countries, textile industry takes a significant role for the Indian economy.

In the recent years, the Indian textile industry had been facing a severe recession in terms of employment, which continued despite fundamental changes in tariff structure among other policy aspects in the mid-1980s and in 1991, though there are symptoms of recovery of late. The output, wages and fixed capital stock have been growing consistently during the past four decades in real terms in the textile industry as a whole.[1]

The trend in the growth of employment is, however, not uniform. Though employment has grown on an average after the reforms of 1991, this is nowhere comparable to the growth of the other variables, especially that of capital stock. This is even more transparent if we examine the period from 1980-81 to 1997-98, when employment has fallen at approximately an annual average rate at which output has grown, despite a remarkable annual growth of capital of over 8%. It would seem from this that, as a whole, textile industry is characterised by a substitutability between capital and labour. Given the labour-intensive nature and unionised labour of the organised segment of this industry, entrepreneurs might have had capital to substitute the labour. Even then, the absolute fall of 5% per year in the employment when output has increased by 5% per year draws attention.

Table 2 shows that the textile industry, on an average, has precisely become much less labour-intensive than it was thirty years ago. An unclear trend in labour-capital ratio casts doubt about the existence of substitutability between capital and labour. However, a rise in this ratio despite a fall in capital productivity seems to suggest the existence of mere substitution of labour by capital, though at an aggregate level, as explained by Ghose (1994).

The fall in aggregate employment could have been partly because of the

[1] See Table 1 for this aspect.

heterogeneity of the textile sector, that might render invalid the attribution of any characteristic to the aggregate industry. For example, despite an existence of substitutability between capital and labour at an aggregate level, rise in capital stock might have as well caused a rise in employment owing to the fact that the former characteristic does not hold true for many disaggregated sub-sectors within the textile industry. The observed fall in employment, in addition, may be attributed to the changes in wages, shocks in demand for the textile products, labour market structure, productivity, degree of openness, tariff structure, trade restrictions and various regulations.

The major objective of the study is to determine the causes of fall in employment in the organised segment of the Indian textile industry. The questions that are required to be addressed for this purpose are to analyse the effects of the factors mentioned above on employment in this industry and to examine the existence of tradeoff between environment and employment in the Indian textile industry, by determining the impacts of environmental regulations on the employment. A dynamic panel framework encompassing various sub-sectors and states to capture the effects structure as well as state-specific factors of the industry is used, in order to capture the existence of rigidities in the labour market.

Our results document the following. Wages have a negative effect on the employment, implying the fact that employment in the textile sector is more or less determined by the labour demand. The output demand shock has a positive effect on employment, indicating the counter cyclical nature of the markup in the Indian textile industry, implicitly hinting the existence of imperfect competition in this industry. The positive effect of capital stock is significant in all estimated models, supporting the hypothesis that the elasticity of substitution between capital and labour in the textile industry is too small to counter the product demand elasticity. Moreover, capital utilisation and liberalisation have positive effect on employment. We also find the existence of negative impact of labour regulations and customs structure and positive impact of environmental regulations and phasing out of MFA quotas on employment.

The paper is organised as follows: Section 2 presents a brief review of literature. Section 3 develops a theoretical framework for this study. Section 4 explains the data sources and variables. Section 5 elucidates the econometric methodology adopted and the results are given in Section 6. Section 7 concludes with some policy implications.

2 Literature Review

Most of the empirical studies dealing with determinants of employment concentrates on the production function framework with cost minimisation, or equivalently, profit maximisation. However, some researchers attempt to pinpoint the effects of certain policy aspects and variables.

Bhalotra (1998b), using the data from organised manufacturing sector from India, documents significant positive effects of capital stock, lagged employment and output change, and negative effects of manhours and previous period wages on the employment. However, the author claims that beyond a threshold level, growth in manhours would enhance employment, and hence it would terminate the puzzle of jobless growth in future.

However, Goldar (2000) shows that employment in organised manufacturing sector grew at 4.03 per cent per annum during the first half of the 1990s; this growth has taken place despite the prevalence of unaltered statutory regulations impacting on employment decisions of the firms, possibly owing to the change in the size structure in favour of small and medium industries and the slowdown in the growth in real wages.

Nagaraj (2004) shows a fall in employment of workers as well as their earnings in the late nineties, which is attributed to employers' augmentation of output by work intensification that pushes output towards the marginal productivity curve, at the same time extending the frontier outwards by augmenting capacity. Such a process was perhaps possible only when the labour market is flexible enough to accept the terms and conditions laid down by employers. Deshpande and Sarkar (2004) and Debroy (1997) are other major studies on labour flexibility and reforms in India.

Fallon and Lucas (1993) studies the effects of job security legislations, namely, the amendments done in 1976 and 1982 to the Industrial Disputes Act of 1948, on dynamic labour demand in the industries that are covered in census and sample sector of the Annual Survey of Industries in India. The results show that the labour demand in the large scale industries suffered more compared to the small scale units thus indicating the dependence of the effects of regulations on the scale of operation as a notion of implementability. Further, even among the large scale units, the negative effect of job security legislation on employment is low with a relatively less unionised labour force.

On the other hand, Ghose (1994) shows that employment in organised manufacturing sector had been falling in the mid-1980s due to the increased cost of labour as compared to that of capital resulting in a substitution of labour by capital due to increased capital-intensive nature of the production. Roy (1998a), analysing the ASI data for the period 1960-61 to 1993-94, finds that job security regulations, considering both 1976 and 1982 amendments, have not been responsible for slow down in employment growth.

Berman and Bui (2001) analyses the effects of environmental regulation on the labour demand. This study estimates employment effects of sharply increased air quality regulation in Los Angeles. The authors find no evidence that local air quality regulation substantially reduced employment, despite allowing for induced plant exit and dissuaded plant entry, partly because regulated plants are not in labour-intensive industries. Similarly, Goodstein (2002) argues that there is no trade-off between environmental regulations and jobs in USA at a macro level in the long run. The new jobs created for implementation of regulations might more than compensate the job loss due to them, as seen in the employment data of the USA.

Rana and Ramaswamy (2003) report a positive impact of trade liberalisation and degree of flexibility of labour regulations across states and sectors on the labour-demand elasticities in the Indian manufacturing sector. According to this study, the trade reforms of 1991 have positive effects on the labour demand elasticity directly and indirectly through those on impacts of degree of flexibility of labour regulations.

Besley and Burgess (2004) investigate whether the industrial relations climate in Indian states has affected the pattern of manufacturing growth in the period 1958-92. They show that states which amended the Industrial Disputes Act in a pro-worker direction experienced lowered output, employment, investment and productivity in registered or formal manufacturing sector.

Dev (2000) examines the impact of economic liberalisation on employment and labour incomes in South Asia based on a Computable General Equilibrium (CGE) model. The results indicate a higher growth of employment in informal and private sectors despite a jobless growth in the 1980s.

This indicates that labour rigidities have affected the employment growth. However, growth rate of organised manufacturing sector has increased in the post-reform period, while that of the unorganised part has fallen.

Uchikawa (2003) shows that though the removal of labour market rigidities that arise from reforms in India has caused a change in the structure of the labour market. However, this has not necessarily resulted in a decline in the employment. This is because of the enhanced investment owing to the reduced regulations, which might have progressive effects on employment. Unni (2003) suggests a post-reform shift of labour force from the organised to unorganised sector despite an existence of positive linkages between them. However, Ramaswamy (2003) does not find sufficient evidence for this hypothesis, since the differentials in *real* wages are not widening.

Roy (2003) notes that the overall job loss in the organised sector was limited to certain industries with old roots and in old industrialised states in the 1990s. Most of the so-claimed decline in employment post-1991 was owing to reallocation of labour from such sectors to profitable sectors. The industries that survived in declining sectors could do so by going for subcontracting and plant-level bargaining. Further, taking a trade-union's perspective, ILO-ARTEP (1989) argues that decline of employment in organised textile sector in India was because of structural change as a result of product preferences, modernisation and deliberate labour reduction by many mills to cut costs.

Based on a field survey, Howell and Kambhampati (1999) examine the impact of liberalisation on labour in cotton textile mills of Ahmedabad. With their small scale of production, poorer wages and working conditions and lower tax payments, the powerlooms gave competition to composite mills. Because of competition, many composite mills in India were closed even before liberalisation. This phenomenon got accentuated after liberalisation, resulting in the closure of 82 per cent of all mills between 1994 and 1996 and 80 percent decline in the workforce.

From the above review, we infer that the growth of employment has been falling in the Indian manufacturing sector on an average for about the past three decades owing to real wage growth, various regulations, substitution of labour by capital to some extent, low capital utilisation, and a shift of the labour force from organised to unorganised segment of the manufacturing sector. However, none of above-mentioned papers have focussed on the textile industry using sector-specific data. We, in this paper, have tried to analyse this. Further, the uniqueness of this study lies in modelling the effects of MFA quota utilisation, customs structure, labour and environmental regulations on employment. In the following section, we develop a theoretical model to justify our empirical exercise.

3 Theoretical Framework

This section is divided in two parts: first develops a static model, whereas the second one provides a dynamic version.

3.1 A Model of Static Profit Maximisation

The production function of a representative firm in the Indian textile sector, with three inputs, namely capital stock (K), labour (L) and an index of technical progress (A).[2], is assumed to take the Cobb-Douglas functional form for simplicity[3] From these inputs, environmental emissions (z) caused by the production of the good (y) can be considered as a function of a fraction θ of the output, which is allocated for pollution abatement, as in Copeland and Taylor (2003). Hence the production technology is given by:

$$y = (1-\theta)A^{\alpha}K^{\beta}L^{\gamma} \tag{1}$$

$$z = \phi(\theta)A^{\alpha}K^{\beta}L^{\gamma} \tag{2}$$

where $\phi : (0,1) \rightarrow (0,1)$ and $\phi'(\theta) < 0$.

This definition justifies that higher allocation of resources in pollution abatement results in lower level of emissions. For simplicity, a specific structural functional form is assumed for $\phi(\theta)$ given in equation (3), resulting in equation (4), in conjunction with equation (1). As the environmental emissions z are a function of the resources allocated to reduce pollution (θ), an assumption that θ is an increasing function $(\omega(r))$ of the environmental regulation (r) [4], would lead to the equation (5).

[2]By defining A as an independent input, neither of the following is assumed: Neutral ($Y = Af(K,L)$), capital-augmenting ($Y = f(AK,L)$) or labour-augmenting ($Y = f(K,AL)$)technical progress.

[3]Empirical Specifications of Translog form have been tested and yielded poor results, validating the choice of Cobb-Douglas form.

[4]Though Pargal and Huq (1997) find no significant impact of inspections on emissions based on plant-level data from 1990 to 1994, Kathuria (2004) shows evidence for the impact

$$\phi(\theta) = (1-\theta)^{\frac{1}{\delta}} \tag{3}$$
$$y = z^{\eta}(A^{\alpha}K^{\beta}L^{\gamma})^{(1-\delta)} \tag{4}$$
$$y = \omega(r)^{\eta}(A^{\alpha}K^{\beta}L^{\gamma})^{(1-\delta)} \tag{5}$$

The profit maximisation problem of the representative firm, assuming an imperfect competition, is given in equation (6). The first-order condition with respect to employment is given by equation (7) and is simplified to equation (8) by taking the price elasticity of output as η and the nominal costs of labour, capital and emissions controlled (E) as W, i and c respectively.

$$max\Pi = p\omega(r)^{\delta}(A^{\alpha}K^{\beta}L^{\gamma})^{(1-\delta)} - WL - iK - c\omega(r) \tag{6}$$
$$\frac{\delta\Pi}{\delta L} = 0 : W = p\frac{\delta y}{\delta L} + y\frac{\delta p}{\delta y}\frac{\delta y}{\delta L} \tag{7}$$
$$\frac{\delta y}{\delta L}p(1+\frac{1}{\eta}) = W \tag{8}$$

Equation (8) assumes price setting[5] and perfect labour market that facilitate the choice of wages to be considered as a result of the profit maximisation problem. In a study that estimates the determinants of employment, nominal wages, prices, and labour force by using a dynamic simultaneous equations model across seven states of Australia, Chaudhuri and Sheen (2003) take price change as endogenous. However, according to Fallon and Lucas (1993), this framework may not be relevant for Indian context, since the quasi-fixed factor demand functions need not depend on profit maximisation problem. Wages are mostly determined as a result of collective or tripartite bargaining, prices by market interactions and labour force by various socio-economic as well as demographic factors in India.

However, we can relax this assumption by incorporating rigidities R, capturing all the distortions in the labour market including the difference between the market wages and actual wages. Given this, we obtain equation (9) by taking ν as mark-up.[6]

of informal or media-based regulation on pollution in Gujarat, substantially validating this assumption.

[5]Chakrabarti (1977), Chatterji (1989) and Bhalotra (1998a) provide evidence for existence of mark-up-based price setting in Indian industries.

[6]It can be shown that mark-up is $\nu = \frac{1}{1+\frac{1}{\eta}}$ and is a function of demand shock σ^{e}.

The rigidities R may arise due to the presence of the labour regulations and expenditure incurred in social security directly and or because of the trade restrictions (or liberalisation leading to their reduction) indirectly as their restrictive effect on the institutional features of the labour market may affect employment and wages.[7] The partial derivative of output with respect to employment is given in equation 10 in terms of the real wages expressed as w.

Expanding equation (10) using the explicit expression of $\frac{\delta y}{\delta L}$, which is given in equation (11), the labour demand function can be obtained as shown in equation 12.

$$\frac{\delta y}{\delta L} p \frac{1}{\nu(\sigma^e)} = WR \tag{9}$$

$$\frac{\delta y}{\delta L} = wR\nu(\sigma^e) \tag{10}$$

$$\frac{\delta y}{\delta L} = z^{\delta}(1-\delta)(A^{\alpha}K^{\beta}L^{\gamma})^{(1-\delta-1)}\gamma L^{\gamma-1} \tag{11}$$

$$L = \left(\frac{wR\nu(\sigma^e)}{A^{(1-\delta)\alpha}K^{(1-\delta)\beta}\gamma(1-\delta)\omega(r)^{\delta}}\right)^{\frac{1}{\gamma(1-\delta)-1}} \tag{12}$$

From equation (1), the elasticities of output with respect to labour, capital and technical progress, denoted by ϵ_L, ϵ_K and ϵ_T are γ, β and α multiplied by $(1-\delta)$ respectively. Using this, we can write equation (12) as:

$$L = \left(\frac{1}{\epsilon_L}\right)^{\left(\frac{1}{\epsilon_L - 1}\right)} (Rw\nu(\sigma^e))^{\left(\frac{1}{\epsilon_L - 1}\right)} (\omega(r)^{\delta} A^{\epsilon_T} K^{\epsilon_K})^{\left(\frac{1}{1-\epsilon_L}\right)} \tag{13}$$

To examine the comparative statics, it would be useful to observe that the elasticities of output with respect to capital and labour are positive and less than unity, as empirically observed[8], and that to technical progress need not be positive, [9], though it may be expected to be so. If the first term in

[7] For example, Dutta (2004) finds that the impact of protection on the inter-industry wage premia is substantially positive. Workers employed in industries with high tariffs receive higher wages than apparently identical workers in low tariff industries.

[8] Based on the regressions of logarithm of output against that of capital and that of labour force

[9] This is because of the fact that there is no variable that captures it explicitly, necessitating the use of time dummies to capture, which have positive/negative effects for different years

equation 13 is denoted by a constant a and $\frac{1}{1-\epsilon_L}$ is denoted by b[10], equation (13) can be simplified as follows:

$$L = a(Rw\nu(\sigma^e))^{-b}(\omega(r)^{\delta}A^{\epsilon_T}K^{\epsilon_K})^b \tag{14}$$

The partial derivatives of the labour demand function with respect to wages, capital, technical progress, demand shock, labour regulations, trade restrictions and environmental regulations can be derived from equation (14) and presented in equation (15) - equation (20). From equation (15), we can infer that labour demand is clearly decreasing in wages.[11] As long as the elasticity of output to labour demand is less than one, increase in wages should result in fall in employment.

$$\frac{\delta L}{\delta w} = a(-b)w^{-b-1}(R\nu(\sigma^e))^{-b}(\omega(r)^{\delta}A^{\epsilon_T}K^{\epsilon_K})^b < 0 \tag{15}$$

The partial derivative of labour demand with respect to rigidities (as in equation (16)) reveals that labour demand is decreasing in rigidities caused by labour regulations and trade restrictions. The reason is that as long as the elasticity of output to labour demand is less than one, increase in the rigidities that keep wages higher than equilibrium should result in fall in employment.

$$\frac{\delta L}{\delta R} = a(-b)R^{-b-1}(w\nu(\sigma^e))^{-b}(\omega(r)^{\delta}A^{\epsilon_T}K^{\epsilon_K})^b < 0 \tag{16}$$

Effect of technical progress on employment depends on the elasticity of output with respect to technical progress (ϵ_T), as shown in equation (17), which may be positive or negative. In fact, as Bhalotra (1998b) notes, labour-augmenting technical progress would have ambiguous effect on labour demand while capital-augmenting or neutral technical progress would be expected to have positive effect on it. Since the type of technical progress itself may vary over years, this needs to be determined empirically.

[10] Note that a and b are always positive

[11] As $-b$ is negative and all other terms are negative.

$$\frac{\delta L}{\delta A} = a(wR\nu(\sigma^e))^{-b}(\omega(r)^{\delta}K^{\epsilon_K})^b\epsilon_T bA^{\epsilon_T b-1} \tag{17}$$

Effect of capital on employment depends on two effects, namely, the positive elasticity of output with respect to capital and the ambiguous effect of technical progress on labour demand, as shown in the two terms in equation (18). While the former is a clear indication of complementarity between capital and output, the latter offers an explanation for substitutability of labour by capital, assuming that technical progress is increasing in capital and labour demand is decreasing in technical progress or technical progress is decreasing in capital and labour demand is increasing in technical progress.[12]. Hence, examination of existence of complementarity between capital and labour is yet another open question for empirics.

$$\frac{\delta L}{\delta K} = a(wR\nu(\sigma^e))^{-b}((\omega(r)^{\delta}A^{\epsilon_T})^b\epsilon_K bK^{\epsilon_K b-1} + \frac{\delta L}{\delta A}\frac{\delta A}{\delta K} \tag{18}$$

Environmental regulations may cause a fall or rise in labour demand based on whether labour demand is increasing or decreasing in emissions, since we can assume the latter to be as a decreasing function of environmental regulations, so that $\omega'(r) < 0$.

$$\frac{\delta L}{\delta r} = \frac{\delta L}{\delta\omega(r)}\omega'(r) \tag{19}$$

To explain the effect of environmental emissions on labour demand, their effect on other variables in this framework should be known. Porter's hypothesis states that their reduction would enhance technical progress and output by means of reduced costs and increased efficiency in production. However, emissions may also be reduced by lockouts or reduction in production of polluting output, thus making the effect of emissions on output ambiguous. Compliance with the regulation might lead to higher employment because of the requirement of labour in the activities of abatement and control of pollution for compliance. Whether capital is decreasing or

[12] If $\frac{\delta L}{\delta A} < 0$ and $\frac{\delta A}{\delta K} > 0$ or if $\frac{\delta L}{\delta A} > 0$ and $\frac{\delta A}{\delta K} < 0$, term 2 in equation (18) is an indication of substitutability of labour by capital

increasing in emissions is an empirical issue, since controlling the emissions may lead to lockouts or investments to abate. In short, effect of environmental regulations depends on its effect on output, capital and technical progress. If Porter's hypothesis holds, then $\frac{\delta L}{\delta \omega(r)} < 0$, then labour demand is increasing in environmental regulations. On the other hand, if the environmental regulations are restrictive and distortional in nature, labour demand is decreasing in environmental regulations.

Demand shock affects employment through the cyclicity of markup, as shown in equation (20). If mark up is countercyclical, then a positive demand shock is reinforced by means of a decreased markup so as to raise the employment and a negative demand shock is worsened because of an increased markup, consequently reducing the employment. This is in line with the inference from the equation (20) that if $\nu'(\sigma^e) < 0$, then $\frac{\delta L}{\delta \sigma^e} > 0$ as $-b < 0$. Similarly, a procyclical markup would result in demand shock affecting the employment negatively.

$$\frac{\delta L}{\delta \sigma^e} = a(Rw)^{-b}(-b)\nu(\sigma^e)^{-b-1}\nu'(\sigma^e)(\omega(r)^{\delta} A^{\epsilon_T} K^{\epsilon_K})^b \tag{20}$$

A logarithmic transformation of equation (14) gives us econometrically estimable specification, including mandays ($logd$) as a control variable, with i and t representing the sub-sector and time respectively as:[13]

$$\begin{aligned} logL_{it} = \alpha_0 + \alpha_1 logw_{it} + \alpha_2 logk_{it} + \alpha_3 dlogy_{it} + \\ \alpha_4 r_{jit} + \alpha_5 l_{kit} + \alpha_6 logd_{it} + \beta_i + \gamma_t + u_{it} \end{aligned} \tag{21}$$

In equation (14), labour demand was expressed in terms of capital and other factors, implicitly assuming that the level of capital is determined exogenously. This is capital-constrained model of employment. Alternatively, we may assume that the level of output is exogenous leading to an output-constrained model of employment.

[13]We assume that the markup is a linear function of demand shock σ^e without intercept ($\nu = \tau\sigma^e$), exponential change in output (y_t/y_{t-1}) to be a proxy for the demand shock σ^e, the environmental emissions $\omega(r)$ to be an exponential function of the dummies for environmental regulation r_j ($\omega(r_j) = e^{r_j}$), index of technical progress to be an exponential function of time ($A_{it} = e^{\gamma t}$)and labour market rigidity to be an exponential function of various proxies and dummies for labour regulation and trade restriction/liberalisation l_k ($R = e^{l_k}$) used in the study.

Output-constrained model of employment can be derived using equation (13), by multiplying the numerator and denominator of the left hand side by $L^{\frac{\epsilon_L}{\epsilon_L - 1}}$ and simplifying using equation (4), implying the following:

$$L = (\frac{wR\nu(\sigma^e)}{\epsilon_L y})^{(\frac{1}{\epsilon_L - 1})} L^{\frac{\epsilon_L}{\epsilon_L - 1}} \tag{22}$$

$$L = (\frac{\epsilon_L y}{wR\nu(\sigma^e)}) \tag{23}$$

Comparative statics for the output-constrained model of employment is simpler than that for the capital-constrained one, as can be inferred from equation (23), because of the fact that constraining for output renders the inclusion of most variables in the system redundant. As shown in equation (24), labour demand is decreasing in wages in this model.

$$\frac{\delta L}{\delta w} = -\frac{\epsilon_L y}{w^2 R\nu(\sigma^e)} < 0 \tag{24}$$

Labour demand is increasing in output as clearly indicated by equation (25).

$$\frac{\delta L}{\delta y} = \frac{\epsilon_L}{wR\nu(\sigma^e)} > 0 \tag{25}$$

Unlike in the capital-constrained model, the effect of demand shock on employment is not unambiguous in the output constrained model. The first term in equation (26) can be negative or positive depending on whether the markup is procyclical or countercyclical, while the second term is positive as long as the output is increasing in demand shock, which is bound to be the case. If the positive effect of demand shock on output is high enough to outweigh its possible direct negative effect in case markup is procyclical, demand shock affects labour demand positively.

$$\frac{\delta L}{\delta \sigma^e} = -\frac{\epsilon_L y}{wR\nu(\sigma^e)^2}\nu'(\sigma^e) + \frac{\epsilon_L y}{wR\nu(\sigma^e)}\frac{\delta y}{\delta \sigma^e} \tag{26}$$

The effect of rigidities that arise from labour regulations and trade restrictions is clearly negative, as seen in equation (27). This is because of the direct effect reflected by the first term as well as the indirect effect, represented by the second term, is negative.

$$\frac{\delta L}{\delta R} = -\frac{\epsilon_L y}{wR^2\nu(\sigma^e)} + \frac{\epsilon_L}{wR\nu(\sigma^e)}\frac{\delta y}{\delta R} \tag{27}$$

Since the model has considered a representative firm for a time period, there are bound to be sub-sector-specific and time-specific fixed effects, captured by β_i and γ_t, respectively. If the labour demand is output-constrained, the following specification would result from equation (23):

$$\begin{aligned} logL_{it} = \alpha_0 + \alpha_1 logw_{it} + \alpha_2 logy_{it} + \alpha_3 dlogy_{it} + \\ \alpha_4 r_{jit} + \alpha_5 l_{kit} + \alpha_6 logd_{it} + \beta_i + \gamma_t + u_{it} \end{aligned} \tag{28}$$

3.2 A Dynamic Model of Profit Maximisation with Adjustment Costs of Labour

In Indian textile industry, the constraints on firing an employee, that may lead to redundant labour, coupled with the general cyclicality in the industry in terms of booms and recessions, necessitate the modelling the profit maximising behaviour in a dynamic framework. Here the firm would be concerned about the present value of future profits till a time period t_1.[14] The discounting factor q can be considered to be the sum of actual discount rate and the rate of job separation/hiring that costs the firms. Moreover, an explicit functional specification of the costs involved in the adjustment to new employment $(C(\dot{L}_t))$[15], arising out of regulations among other factors, is required, warranting the following form:

$$max\Pi = \int_0^{t_1} [p_t \omega(r_t)^{\delta} (A_t^{\alpha} K_t^{\beta} L_t^{\gamma})^{(1-\delta)} - W_t L_t - i_t K_t - c_t E_t - C(\dot{L}_t)] e^{-qt} dt \tag{29}$$

$$C(\dot{L}_t) = a|\dot{L}_t| + b|\dot{L}_t|^2 : a, b > 0 \tag{30}$$

Assuming that the profit maximisation decision does not take capital and emissions explicitly into consideration, since the former can be considered as being primarily dictated by the industrial licensing process[16] and the latter as a function of regulation.[17] For a dynamic optimisation problem[18], the path equation has to be defined for the state variable, which is, in this model,

[14] This assumes Markov Decision Process.

[15] Note that $C(\dot{L}_t) > 0, C'(\dot{L}_t) > 0, C"(\dot{L}_t) > 0$ and $C(0) = 0$. Gould (1968) proves that this specification captures the higher costs associated with more rapid changes in labour.

[16] Fallon and Lucas (1993) and Mathur (1989) argue this for Indian manufacturing, holding good for textiles also.

[17] Mani and Huq (1996) find that costs of compliance to environmental regulation are not as high as to influence the choice of location. Similarly, to the extent that this can be extended to profit maximisation, emissions that depend on compliance with regulation can be taken as exogenous.

[18] For a detailed description on this, see Intriligator (2002) and Hoy et al. (2001).

labour. Following Gould (1968), under the assumption of static expectations about wages and prices, this can be specified as:

$$\dot{L_t} = \gamma[L^* - L_t] : \gamma > 0 \tag{31}$$

The above equation reflects a partial adjustment mechanism. The control variable in this model is the rate of growth of labour $\dot{L_t}$. Given this, the Hamiltonian function can be expressed as:

$$\begin{aligned} H(L_t, \dot{L_t}) = [p_t\omega(r_t)^{\delta}(A_t^{\alpha}K_t^{\beta}L_t^{\gamma})^{(1-\delta)} \\ -W_tL_t - i_tK_t - c_tE_t - C(\dot{L_t})]e^{-qt} + \lambda(t)\dot{L_t} \end{aligned} \tag{32}$$

We assume that the first term in $H(L_t, \dot{L_t})$ is differentiable and jointly concave in L_t and $\dot{L_t}$ and $\dot{L_t}$ is linear in L_t. From equation (29), we get:

$$\frac{\delta H(.)}{\delta \dot{L_t}} = -(a + 2b|\dot{L_t}|e^{qt}) + \lambda(t) = 0 \tag{33}$$

$$\lambda(\dot{t}) = \frac{\delta H(.)}{\delta L_t} \tag{34}$$

$$L(0) > 0, \lambda(t_1) = 0 \tag{35}$$

Solving equations (33) and (34) and applying the steady state conditions at $t = 0$, we obtain equation (36). The equilibrium employment is given in equation (37) implying that $\dot{L_t} = \ddot{L_t} = 0$.

$$py_L - W_t + 2b\ddot{L}qt - 2b\dot{L}q - aq = 0 \tag{36}$$

$$L^* = (\frac{(w_t + aq/p)}{A^{\epsilon_T}K^{\epsilon_K}\epsilon_L\nu(\sigma^e)\omega(r)})^{\frac{1}{\epsilon_L - 1}} \tag{37}$$

Approximating the growth rate in labour in the form of differences and then simplifying by taking $\Delta t = 1$ and the rigidities $R = aq/p$, the functional form of dynamic capital-constrained model of employment can be expressed as equation (39). Comparative statics of equation (39) demonstrate that labour demand is decreasing in wages and rigidities and increasing in the lag of employment, while the effects of other variables depend on various factors as in the case of static models.

$$\frac{\Delta L_t}{\Delta t} = \gamma[L^* - L_t] \tag{38}$$

$$L_t = \frac{1}{(1+\gamma)} L_{t-1} + \frac{\gamma}{(1+\gamma)} \left(\frac{(w_t + R_t)}{\epsilon_L \nu_t(\sigma^e)\omega_t(r)^\delta A^{\epsilon_T} K^{\epsilon_K}}\right)^{\frac{1}{\epsilon_L - 1}} \tag{39}$$

Further, the dynamic output-constrained model of employment can be derived by first getting the equilibrium level of employment in terms of output and other variables from equation (37) given by equation (40) and then using equation (38) to obtain equation (41).

$$L^* = \left(\frac{\epsilon_L y_t}{(w_t + R_t)\nu_t(\sigma^e)}\right) \tag{40}$$

$$L_t = \frac{1}{(1+\gamma)} L_{t-1} + \frac{1}{(1+\gamma)} \left(\frac{\epsilon_L y_t}{(w_t + R_t)\nu_t(\sigma^e)}\right) \tag{41}$$

Let l_{kit} represent all the proxies and dummies that represent a and q, capturing social security aspects and labour market rigidities respectively. Taking a logarithmic transformation and expressing a part of the first lag of labour in terms of other variables would result in the following econometric specification:

$$\begin{aligned} logL_{it} &= \alpha_0 + \Sigma_{j=0}^{2}\alpha_{1j} logw_{it-j} + \Sigma_{j=0}^{2}\alpha_{2j} logk_{it-j} + \Sigma_{j=0}^{2}\alpha_{3j} dlogy_{it-j} \\ &+\alpha_4 r_{jit} + \alpha_5 l_{kit} + \Sigma_{j=1}^{2}\alpha_{6j} logL_{it-j} + \Sigma_{j=0}^{2}\alpha_{7j} logd_{it-j} + \beta_i + \gamma_t + u_{it} \end{aligned} \tag{42}$$

A Specification corresponding to the static form of output-constrained model would be as follows:

$$\begin{aligned} logL_{it} &= \alpha_0 + \Sigma_{j=0}^{2}\alpha_{1j} logw_{it-j} + \Sigma_{j=0}^{2}\alpha_{2j} logy_{it-j} + \Sigma_{j=0}^{2}\alpha_{3j} dlogy_{it-j} \\ &+\alpha_4 r_{jit} + \alpha_5 l_{kit} + \Sigma_{j=1}^{2}\alpha_{6j} logL_{it-j} + \Sigma_{j=0}^{2}\alpha_{7j} logd_{it-j} + \beta_i + \gamma_t + u_{it} \end{aligned} \tag{43}$$

4 Data Sources and Description

For this study, 32 sub-sectors[19] have been chosen for the textile industry, whose three- digit aggregate national data were obtained from the Annual Survey of Industries (1973-74 to 1997-98). They were broadly classified under six groups, namely, cotton, wool, silk, jute, synthetics and others

[19]The detailed list of these can be obtained on request, though they have not been shown here to save space

irrespective of the actual two-digit National Industrial Classification (NIC-1987). This was done to control for the effects of more relevant groups of sub-sectors. Of these, 8 sub-sectors are in the cotton group, 4 are in wool group, 3 are in the silk group, 3 are in man-made fibres group, 6 in the jute group and 8 in the others. The dependent variable is the logarithm of employment in terms of total persons engaged in the sub-sector.

The independent variables are invested capital stock deflated by the price index of textile machinery, change in output (in particular, change in the logarithm of the gross value of output) as a proxy for demand shock, wages per person engaged in production per year deflated by the sub-sector-specific price index. The data for price indices of different sub-sectors was collected from Chandok and Group (1990) and various statistical publications of the union ministry of labour. The deflator (with 1981 as base year) used for capital stock is the WPI of textile machineries, that used for wages is the CPI for industrial labourers (All India as well as different states), and that used for the output is the commodity specific WPI approximated for the two-digit and three digit NIC-1987. This way of deflating different variables using different indices is consistent with Balakrishnan and Pushpangadan (1998), who advocate this double-deflator method.

We work with natural logarithm of all the variables. In addition to the all-India three-digit industries, four two-digit industries (codes 23 to 26) for 19 states from 1979-80 to 1997-98 are analysed. Measuring capital stock has always been a contentious issue. Though the perpetual inventory method being followed by many researchers, according to Ray and Bhattacharya (2003), this does not take care of both the problems, as inclusion of depreciation is not reliable as it is mostly reported as an accounting identity, however exclusion of it gives rise to an incomplete measure.

Book Value of capital stock, which is available in the ASI database, may be poorly correlated with the actual capital stock. The measure of capital stock, as required for any study based on production function, should be that of the actually utilised part, which necessitates the exclusion of the idle capital.

We proceed by considering the total invested capital[20] (K_{git}) that is

[20]Other measures including Gross and Net Fixed Assets, Gross Productive Capital and Net Capital Stock calculated by implicit deflator method were found to be highly correlated with each other. Results are robust to the use of different measures.

the sum of physical and working capital and then subtracting depreciation (d_{git}) from this, resulting in the net invested capital (NK_{git}). Utilised part of net invested capital is then obtained by multiplying this by the capacity utilisation rates (U_{git}). This exercise is summarised in the equations below:

$$NK_{git} = K_{git} - d_{git} \tag{44}$$

$$UNK_{git} = NK_{git} * U_{git} \tag{45}$$

Two different measures of capacity utilisation are developed and used in this study. One of them uses the data from various annual books of the compendium of textile statistics, handbook of textile statistics and manmade fibre statistics. The final measure of capacity utilisation was obtained only for four categories: cotton spinning, cotton weaving, cotton textiles and synthetic fibres. For cotton spinning, it is the ratio of average operating spindles per shift to the total installed spindles. For cotton weaving, it is the ratio of average operating looms per shift to the total installed looms. In the case of man-made fibres, it is the average ratio of the total production to the total installed capacity of production of viscose, polyester, nylon, polypropylene and acetate.

This measure of capacity utilisation developed for the aforementioned sectors was then used as proxy for that of each of the different sub-sectors and for those for which they were clearly found not to be matching, it was assumed to be one. This also assumes that the differences in the utilised capacity during different shifts in a day can be ignored, validating the use of their average to develop this measure. Another measure of capacity utilisation is more rigorous and is constructed from the data available based on the following equations that contain all variables in their real terms. They clearly define capacity utilisation for any year and sub-sector as the output-capital ratio for that year expressed as a percentage of the maximum output per capital achieved for that sub-sector over time.

$$YK_{git} = Y_{git}/K_{git} \tag{46}$$

$$MAXYK_{gi} = max(Y_{git}/K_{git}) \tag{47}$$

$$U_{git} = YK_{git}/MAXYK_{gi} \tag{48}$$

Apart from these variables, in different regressions, time dummies, group dummies, sub-sector dummies and post-1991 dummies have also been included. To capture the effects of trade liberalisation, degree of openness for different sub-sectors for the period of analysis have been included by an interpolation of available data in Pandey (1999). The degree of openness are in terms of ratio of imports to the GDP, ratio of the sum of exports and imports to the GDP and the Trade Competitiveness Index (TCI). Apart from these, an average of the last two measures has also been tried as a proxy for degree of openness. Interaction dummies formed by the products of all these dummies and wages have been included in some specifications.

However, since the interpolation exercise may be questionable and none of these indices fit in the specific scenario of textile trade that involves MFA quotas, two additional measures of trade liberalisation or restrictiveness that are specific for the Indian textile industry have been used. One of them is the average percentage utilisation of MFA quotas of apparel exports from India.

We expect to test the proposition that that higher the apparel quota utilisation, higher is the output in most sub-sectors in the textile sector and hence the higher is the employment. If this is true, it can be inferred that with the phasing out of quotas, employment is bound to increase as there would be less or no quotas to begin with. The second measure is the customs duties collected per unit production of different sub-sectors. This reflects, to a large extent, the aspect of distortions to trade owing to the tariff structure. The lower the average customs duty, the higher is the degree of trade liberalisation. The data on MFA quota utilisation rates was collected from different sources, including Uchikawa (1998), Sastry (1984) and Jain (1988), which, in turn, have cited the issues of statistics of trade published by Apparel Export Promotion Council (AEPC).

As for the variables pertaining to labour regulations, different variables were constructed for this study. One of them, following Downes (2002), is the ratio of total non-wage benefits to the average emoluments per person engaged. Secondly, the index of labour regulation developed by Besley and Burgess (2002) for different states has been used. The other variables include the dummies for different years in which there were significant changes in the labour regulations in the country, as mentioned in Ministry of Labour

(2004).[21]

Owing to lack of a comprehensive data for the environmental regulations and their implementation in the Indian textile industry, we proceed as follows: the first set of dummies for the environmental regulation based on the Environment Act (1986) (denoted as *envreg*1) and the ban on Azo dyes (denoted as *polln*1) imposed by Germany in 1996, equals one for those

sub-sectors that directly come under these regulations. We also create another set of dummies treating all sub-sectors equally (denoted by *envreg* and *polln* respectively), assuming inter-linkages of the effects. The significance of the effects of latter set coupled with the insignificance of those of the former set would mean that environmental regulation has not affected the entire textile sector, but only a small section of it.

5 Methodology

Our estimation equation follows directly from the model as outlined in section 2.[22] The four basic models estimated[23] in this study are specified in section 2.

Baltagi (2001) notes the possibility of least squares estimation being inefficient owing to the presence of first order autocorrelation in the error term for a model with lagged dependent variable and to the correlation of the lagged dependent variable with the individual heterogeneity term. The 'within' transformation results in biased estimates. However, in absence of second-order autocorrelation in the errors, the Generalised Methods of Moments (GMM) gives efficient estimates. Arellano and Bond (1991) present specification tests for the Generalised Method of Moments (GMM) estimation of dynamic panel data. The GMM estimator is significantly more

[21]Some of them are Payment of Gratuity Act 1972, Equal Remuneration Act 1976, Interstate Migrant Workmen Act 1979, Child Labour (Prohibition and Regulation) Act 1986, Labour Laws(Exemption from Furnishing returns and Maintaining Registers by certain Establishments) Act 1988 and Employees' Pension Scheme 1995.

[22]DPD package of the OX console software was extensively used in addition to Stata. See Doornik and Ooms (2001) for an introductory guide to Ox Console Software.

[23]Before estimating, Johansen's cointegration and Vector Auto Regression (VAR) analysis of capital, output, labour and TFP were done for the aggregate textile industry from 1960 to 2000. Though no long-run relationship could be established between employment and other variables, impulse response functions suggest a 'dynamic' substitutability between capital and labour and a positive effect of output shock on employment. Further, existence of a long-run relationship between output and capital validates the use of output-constrained and capital-constrained models to check the robustness of the results.

efficient than the Instrumental Variable (IV) method[24], as it uses all potential instruments and produces well-determined estimates in the dynamic panel data models.

Ahn and Schmidt (1995) and Ahn and Schmidt (1997) show that Arellano and Bond (1991) has not used a few additional moment restrictions under the standard assumptions of dynamic panel data model. Wansbeek and Bekker (1996) show that adding moment restrictions minimises the efficiency loss of the GMM estimator as compared to the Maximum Likelihood (ML) estimator. Blundell and Bond (1998) shows that the estimation of the dynamic error component model is a better alternative to the standard first differenced GMM estimator of Arellano and Bond (1991). It is the system GMM estimator deduced from a system of equations in first differences and in levels. This estimator is defined under extra moment restrictions that are available under reasonable conditions relating to the properties of the initial condition process. Exploiting these extra moment restrictions offers efficiency gains and permits the identification of the effects of time invariant variables.

Further, Blundell et al. (2000), Blundell and Bond (2000) and Judson and Owen (1999) present theoretical arguments as well as empirical exercise including Monte-Carlo evidence to prove that the system GMM estimator, which relies on relatively mild restrictions on the initial condition process, is asymptotically more efficient[25] than the standard GMM estimator.

In fact, Alvarez and Arellano (2003) proves that GMM estimators are consistent when $T/N \to c \in (0, 2]$ and more importantly, they are less biased than Within-Group estimators if $T < N$, which is the characteristic of the data used in this study. Though there are numerous bias-correction methods such as those developed by Kiviet (1995), Kiviet (1999), and Bruno (2004), these are for models with low T and much higher N, which may, for example, hold good for short time-series firm-level data and not for longer time-series sub-sectorwise data, such as that used in this study. Carree (2001) develops a method to estimate almost unbiased estimator for a dynamic panel data model, which, however, does not contain any exogenous variable and hence unsuited for this study. Hahn and Kuersteiner (2002) gives the bias for

[24] See, for example, Anderson and Hsiao (1981) and Anderson and Hsiao (1982)

[25] Wansbeek (2001) provides estimators that are more efficient if there are serious measurement error in the variables.

instrumental variable estimation of dynamic panel model when both n and T are large, which again does not hold for this study as both of these are less than 50 for the data used here.

An interesting study by Hayakawa (2005) shows that system GMM is estimator less biased that first-differencing and level-GMM estimators because of the fact that the bias of the former is a weighted sum of the biases in opposite directions of the latter ones. He further notes that if the coefficient on the lagged dependent variable is around 0.5, then system GMM estimator is much less biased than others. Hence, we use the system GMM estimation for this study and the two equations that we estimate are (42) and (43), respectively for capital- and output-constrained employment models, in addition to these equations expressed in differences. We examine the validity of the estimated models using the specification tests.[26]

The two-step GMM estimators, despite being more efficient than their one-step counterparts, result in downward biased estimates of standard errors.[27] A finite sample correction method developed by Windmeijer (2005) is used in this study to work out the standard errors of the two-step estimates. We define valid instruments and instrument matrices[28] for the lagged dependent variable.

However, Alvarez and Arellano (2003) notes that there is no real advantage of GMM when T and N are of a similar dimension, and that within-groups is clearly better when $T > N$.[29] Further, Bun and Kiviet (2005) notes that in small samples of models with dynamic feedbacks, method of moments and least squares estimates are biased, as the former is more biased with higher number of moment conditions employed. Hence, most of the results obtained from system GMM estimation are cross-checked with the bias-corrected within group estimates, using Bruno (2004).[30] We set

[26] Hansen's Over-identification test statistic is asymptotically distributed as χ^2 under the null of instrumental validity with as many degrees of freedom as there are overidentifying restrictions. $AR(2)$ statistic is distributed as standard normal under the null of no second order autocorrelation.

[27] Alternatively, consistent testing procedures developed by Andrews and Lu (2001) could be used if the sample size is high.

[28] However, choosing the optimal number of instruments has not been done this study, because the theoretical literature pertaining to this issue does not consider GMM methods. See, for example, Donald and Newey (2001).

[29] Author is grateful to Prof. Arellano for his personal clarification on this issue by e-mail.

[30] Clarifications provided on this issue by J. Kiviet and F. Windmeijer to the author by e-mail, as well as the code of Stata program xtlsdvc.ado, provided by G. Bruno are

this bias correction method to use Anderson and Hsiao (1982) for initial estimators, to run 100 repetitions for bootstrapping standard errors, assuming normal distribution, and to correct the bias with the accuracy of approximation being of order $1/NT$. This is to incorporate the fact that invoking higher-order terms yields some minor improvements in dynamic panel models with exogenous regressors when N and T are 2 digit numbers, as documented by Bun and Kiviet (2003).

To test for the for serial correlation in the idiosyncratic errors of our panel-data model while performing the estimation given by Bruno (2004), we follow the method discussed by Wooldridge (2002). Drukker (2003) presents simulation evidence that this test has good size and power properties in reasonable sample sizes.

6 Results

The results for the static panel data model (equation (21)), although not reported,[31] show that the wage ($logw_{it}$) has negative effect, consistent with the theory. The demand shock ($dlogy_{it}$) has positive effect, revealing a counter-cyclical markup. The capital stock ($logk_{it}$) also has a positive effect. However, the estimation the static model is not appropriate given the presence of significant first-order as well as second-order autocorrelation. Further, the problem of omission of dynamic effects arising out of adjustment costs would not be eliminated even if we control for autocorrelation. Hence, the dynamic model of employment needs to be estimated, following the theory discussed in section 3.2.

Tables 3 to 6 contain the results of the dynamic panel data regressions using system GMM method. In all these tables, it should be noted that the instruments are valid as revealed by the Hansen's over-identification test and the autocorrelation is present at the first order and absent at the second order, as required for the validity of this technique.

In all these regressions, different measures of capitalstock and capacity utilisation, which have been mentioned in section 4, have been used and the results are almost similar for all the alternative measures. However, for the sake of uniformity, in all the results reported, $logk_{it}$ represents gross

acknowledged with thanks.

[31] It is available on request from the author.

capital stock and *util* represents the measure of capacity utilisation that is constructed based on capital-output ratio. Further all these regressions were carried out by defining the first lag of $logn_{it}$ and levels of other major variables, whose lags are also included, have been defined as GMM-style instruments for both level and difference equations and the other variables, whose lags are been included, have been defined as IV-style instruments.

Table 3 presents the results of estimation of the Capital Constrained Employment Model using All-India Three-Digit Data. Column 1 shows the results with only group dummies included in addition to the major variables of this model. These results show that employment depends significantly on two of its lags, demand shock and capital stock positively. [32] The coefficients of lags of dependent variables (LDVs) are positive.[33] The impact of wages on employment is negative and significant, indicating that employment in textile industry is more or less demand-driven. These results are robust to including year dummies in addition to group dummies (Column 2), year dummies and capital utilisation (Column 3). Column 3 also shows that environmental regulation has significantly enhanced employment, which is an observation consistent with Goodstein (2002), indicating the validity of Porter's hypothesis. The results of Column 4 shows that manhours have negative insignificant effect on employment and is consistent with Nagaraj (2000).[34] Given the dimension of N and T in our case, we also present the results of bias-corrected LSDV estimation, based on Bruno (2004), in the last column. The results are consistent with the previous results and further shows that capital utilisation positively influences employment.[35]

Table 4 presents the results of estimation of the Output Constrained Employment Model using All-India Three-Digit data. The results broadly show that employment depends significantly on one or more of its' own lags, demand shock and output or on its lag positively, though not in all cases. The effect of wages on employment is negative and significant. While column 2 and 3 show that the ban on azo dyes has affected employment negatively,

[32]It should be noted that the signs of lags of other variables are not interpreted in most cases as we use them mainly as control variables.

[33]This rules out serious classical measurement errors and bias due to an unobserved time-variant co-founder, explained in Mckinnish (2005).

[34]Nagaraj (2000) finds that the multicollinearity between wages and manhours affects the results if both are included simultaneously as the determinants of employment.

[35]The presence of AR(1) validates bias-correction method being used instead of simple within group or LSDV estimates.

domestic environmental regulation[36] appears to have significantly promoted employment, (as reported in column 4 and to some extent in columns 2 and 3). We also note that reforms of 1991 in the Indian economy seem to have enhanced employment (column 2).

Our results so far show that quota utilisation and customs structure do not have significant effects. We attribute this to the fact that these variables as constructed is available for 2-digit industry. Given this, we perform a state-wise 2-digit level analysis. This also allows us to account for spatial heterogeneity and increasing the number of cross-sections. However, this data is available for the period between 1980-81 and 1996-97.

Table 5 presents the results of estimation of the Capital Constrained Employment Model using the state-wise two-digit data. Most of the results are consistent with the results of Tables 3 and 4. However, this analysis gives additional interesting results emerge: Firstly, lags of $logh_{it}$ has significant negative effect in most results in Table 5, showing that the increased utilisation of labour negatively influences employment, as explained in Bhalotra (1998b). Secondly, the labour regulations, as measured by the index developed based on Besley and Burgess (2002) and World-Bank (2002), have a significant negative effect on employment. Thirdly, quota utilisation and the dummy for phasing out of MFA quotas have significant positive effects, while customs structure has a negative significant effect on employment. This result is consistent with the fact that the removal of rigidities would enhance employment. Table 6, showing the results of estimation of the Output-Constrained Employment Model using the state-wise two-digit data, also supports most of the previous results.

In sum, we can infer the following. There is a rigidity in employment in India's textile sector. The negative effect of wages on the employment points towards the fact that employment in the textile sector is more or less determined by the labour demand. The output demand shock has a positive effect on employment indicating the counter cyclical nature of the markup in the Indian textile industry, implicitly hinting the existence of imperfect competition in this industry. The positive effect of capital stock is significant in all estimated models, supporting the hypothesis that the

[36]Note that, as already mentioned in section 4, $envreg1$ and $polln1$ are dummies specific to polluting sub-sectors , significance of whom indicates that environmental regulations have affected employment in them, but not necessarily the entire textile industry

elasticity of substitution between capital and labour in the textile industry is too small to counter the product demand elasticity.

Table 7 shows the average long-run elasticities of employment to capital, output, wages, demand shock and actual manhours. Adjustment speed of employment to shock is found to be around two years, indicating the existence of rigidity in employment. Estimates and standard errors were calculated from the LSDV-BC regressions for the All-India three-digit level data, by the method described in Bhalotra (1998b), setting the coefficient and standard error on the second lag dependent variable to be zero, as this is absent in LSDV-BC regressions. We also note that all the elasticities except that of the mandays are significant.

Table 8 tries to explain employment growth in the textile industry using long run elasticities of employment to wage, capital, manhours and output and their average annual growth rates. We note that in both Capital- Constrained (CCEM) and Output-Constrained (OCEM) Employment Models, though growth in wages alone has contributed quite a high part of fall in employment, almost an equal but positive contribution of growth in capital and output, rendering major part of fall in employment unexplained by these major variables, suggests that various other factors including trade liberalisation and environmental regulations have influenced employment growth in the textile industry.

In order to analyse a few interesting basic policy issues in the Indian textile industry, it is imperative to look at the handlooms and powerlooms sub-sectors in isolation. We further note that it would be also useful to analyse the sub-sectors that are likely to be directly influenced by environmental regulations. These are the wet-processing sectors, which fall under five NIC-87 categories.[37] The results have not reported although available from the authors shows that: in the khadi and handlooms sector employment is not wage-dependent and is rather infulenced by capital, output and other factors. We also obtain positive significant effect of MFA quota utilisation as well as the initiation of phasing out of MFA quotas, negative effect of environmental regulations and positive effect of ban on azo dyes.[38] The results of the powerloom sub-sector indicate that the signs of almost all coefficients

[37]We perform both the system-GMM and bias-corrected within-group estimation.

[38]This is interesting and well-justifiable because Khadi, handloom and other traditional sectors do not use azo dyes and hence could be benefitted by this ban.

are identical to those in the previous results.[39]

We also obtain that for the polluting sectors, domestic environmental regulation has a positive effect on employment, while the external ban on azo dyes has no significant effect. This seems to suggest that the environmental regulations might have either improved the efficiency of the entire process, thereby enhancing output and employment or that the employment might have risen owing to an increased requirement of manpower in order to comply with these regulations.[40]

Absence of an explicit measure of labour regulation warrants for the test for the robustness of the result that labour regulation affects employment using different measures. Here we use the data for number of lockouts[41] by the industries owing to their inability to pay their workers and unrest demonstrated by the workers in terms of mandays lost in strikes. Table 9 shows the results. Most results in this exercise are similar to those in the previous ones. However, there are three interesting inferences in place.

Firstly, the lockouts influence employment positively. This may be because of the possibility that the exit of huge sick industries might have paved way to the opening of new effcient small ones, which enhance employment as observed in Roy (1998b).[42] Secondly, labour unrest affects employment negatively as it is expected *apriori* , since persistent strikes may pave way to firing of workers on disciplinary grounds. Thirdly, wages are insignificant in all specifications in this table, which means one or more of the following: During the period between 1984-85 and 1997-98, employment in textile sector has been wage-independent; or, controlling for the labour unrest and lockouts, wages have insignificant effects on employment, implying that fall in employment cannot be attributed to rise in wages as much as to the other factors considered in this study; or, the effect of wages on employment actually works through the unions, whose behaviour may be reflected in labour unrest and lockouts, rendering the effects of wages *per se* insignificant.

[39] This is based on Prais and Winsten (1954) estimator.

[40] Though there is no empirical support for this, it should be noted that the Environment Act (1986) requires the large-scale polluting industries to set up an 'Effluent Treatment Plant', which in turn, would need some people to establish and run.

[41] It is interesting to note that Besley and Burgess (2004) find a postive correlation between the measure of labour regulation index, strikes and lockouts.

[42] Possibly, sick mills could have rendered many people unemployed because of the inefficiency factor that could restrain the industry from operating at its frontier, in which case it could have employed more people.

7 Conclusion

This paper attempts to examine the role played by various factors on employment in organized textile industry using data from India and her states. We document existence of employment rigidity, negative effect of wages, positive effect of demand shock indicating a counter-cyclical markup, positive effect of 1991 reforms, positive effect of domestic environmental regulation and negative effect of external ban on Azo dyes on employment. Our results are robust to the disaggregation to state-level data. The state-level results, in addition, shows that increase in the manhours worked has been at the cost of fall in employment, positive effect of trade liberalisation in terms of falling customs duties, rise in MFA quota utilisation as well as phasing out of MFA quotas and negative effect of labour regulation on employment.

Further, an analysis in isolation of the pollution-intensive industries seems to support Porter's hypothesis, indicating that environmental regulations might enhance the effciency of process, thereby increasing output and employment. However, the external ban on azo dyes exerts a negative impact on the employment of the industry as a whole, though it has had no impact on the pollution-intensive ones. Moreover, its positive effect on employment in handloom sector suggests that industries that have already complied with the ban by their inherent nature, might perform well because of it. An examination of powerloom sector and handloom sector shows that employment in these sectors were also significantly positively enhanced by trade liberalisation. Powerloom sector seems to be characterised by the independence of employment with respect to output, wages and capital, while that in handlooms is wage-independent.

Given the results of this empirical exercise, we can infer that the employment in the Indian textile sector, encompassing all its sub-sectors, is poised to increase in a post-MFA regime. The environmental regulations need not affect the employment in future and the possible job loss might be compensated by the job requirements arising from the compliance to these regulations. Hence, employment should not be a concern in implementing environmental standards and regulations in the textile sector. Further, policies that enhance trade liberalisation and labour exibility are required to promote employment in the textile industry in India.

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TABLES

Table 1: Average Annual Growth Rates in the Organised Indian Textile Sector (1993-94 prices)

Period	Output	Employment	Real Wages	Real Fixed Capital Stock
1961-62 to 1970-71	5.034	0.496	2.487	3.645
1971-72 to 1980-81	6.668	3.295	2.882	4.643
1981-82 to 1990-91	8.174	-0.968	5.44	8.802
1991-92 to 1999-2000	6.718	0.997	2.378	17.774
1980-81 to 1997-98	5.34	-5.17	5.35	8.11

Source: Author's Calculations based on the ASI data

Table 2: Features of Employment, Capital and Output (1993-94 prices)

Year	Y/K	K/N	Y/N
1973-74	2.569	4.523	11.616
1980-81	3.657	4.364	15.958
1985-86	3.092	7.331	22.664
1990-91	3.614	10.332	37.336
1997-98	1.546	34.122	52.760

Source: Author's Calculations based on the ASI data

Table 3: Capital-Constrained Model: All-India Three-Digit Data.
Dependent Variable: $logn_{it}$

Variable	1	2	3	4	LSDV-BC
$logn_{it-1}$	0.646***(0.000)	0.601***(0.006)	0.382**(0.012)	0.606***(0.001)	0.612***(0.000)
$logn_{it-2}$	0.203*(0.088)	0.228(0.131)	0.456***(0.003)	0.274*(0.075)	
$dlogy_{it}$	0.324***(0.000)	0.349***(0.000)	0.328***(0.003)	0.321***(0.004)	0.193***(0.000)
$dlogy_{it-1}$	0.175*(0.065)	0.228*(0.056)	0.185*(0.075)	0.094(0.438)	0.023(0.513)
$dlogy_{it-2}$	0.005(0.949)	0.018(0.838)	-0.010(0.775)	-0.038(0.522)	0.022(0.355)
$logk_{it}$	0.226***(0.000)	0.180**(0.031)	0.210**(0.013)	0.186**(0.018)	0.361***(0.000)
$logk_{it-1}$	-0.251**(0.033)	-0.260*(0.068)	0.019(0.788)	-0.046(0.45)	-0.102***(0.000)
$logk_{it-2}$	0.085(0.229)	0.127(0.389)	-0.071(0.438)	-0.0095(0.87)	0.024(0.372)
$logw_{it}$	-0.457**(0.024)	-0.430**(0.018)	-0.290**(0.049)	0.003(0.994)	-0.186***(0.000)
$logw_{it-1}$	0.240(0.224)	0.210(0.477)	-0.343(0.214)	-0.300(0.426)	0.129*(0.051)
$logw_{it-2}$	0.185(0.214)	0.123(0.509)	0.434**(0.036)	0.088(0.731)	-0.031(0.589)
$logh_{it}$				-0.150(0.176)	
$logh_{it-1}$				0.345**(0.012)	
$logh_{it-2}$				-0.189**(0.021)	
util			-0.002(0.976)		0.210***(0.000)
polln1		0.040(0.790)	-0.134(0.296)		
envreg1		0.018(0.917)	0.474*(0.052)		
ref		0.024(0.263)			
mfa		-0.004(0.883)	-0.007(0.691)		
secur					
quota			0.000(0.397)		
customs			0.025(0.520)		
Year Dummies	No	Yes	Yes	No	Yes
Group Dummies	Yes	Yes	No	No	No
cons	0.400(0.279)	0.288(0.527)	0.204(0.429)	-0.012(0.891)	
Hansen's statistic	15.410(1.000)	12.06(1.000)	10.480(1.000)	7.6(1)	
AR(1)	-3.010***(0.003)	-2.9***(0.004)	-2.110**(0.035)	-2.49**(0.013)	53.342***(0.000)
AR(2)	-0.230(0.817)	-0.38(0.702)	-1.390(0.163)	0.36(0.722)	

Note: *,** and *** denote significance at 10%, 5% and 1% Levels of Significance, respectively. Figures within parentheses are p-values.

Table 4: Output-Constrained Model: All-India Three-Digit Data.
Dependent Variable: $logn_{it}$

Variable	1	2	3	4	LSDV-BC
$logn_{it-1}$	0.367***(0.004)	0.523***(0.000)	0.203(0.190)	0.417*(0.053)	0.438***(0.000)
$logn_{it-2}$	0.514***(0.000)	0.417***(0.008)	0.283***(0.007)	0.382(0.119)	
$dlogy_{it}$	0.289**(0.021)	0.558***(0.000)	0.156(0.345)	0.520***(0.000)	0.106***(0.011)
$dlogy_{it-1}$	0.343***(0.001)	0.266**(0.013)	0.150*(0.063)	0.036(0.897)	-0.058*(0.062)
$dlogy_{it-2}$		-0.026(0.789)		-0.016(0.869)	-0.022(0.365)
$logy_{it}$	0.146(0.248)		0.361**(0.044)		0.429***(0.000)
$logy_{it-1}$		0.047(0.553)		0.206**(0.011)	
$logy_{it-2}$					
$logw_{it}$	0.087(0.751)	-0.236*(0.083)	-0.335**(0.032)	0.0001(0.999)	-0.230***(0.000)
$logw_{it-1}$	-0.415(0.208)	-0.037(0.867)	-0.181(0.249)	0.186(0.819)	0.058(0.384)
$logw_{it-2}$		0.242(0.220)		-0.409(0.560)	-0.066(0.255)
$logh_{it}$				-0.167(0.233)	
$logh_{it-1}$	0.015(0.118)			0.209(0.185)	
$logh_{it-2}$				-0.037(0.750)	
util				-0.059(0.604)	
polln1	-0.358*(0.055)	-0.257*(0.086)	-0.088(0.418)		
envreg1	0.287(0.109)	0.350(0.110)	0.340*(0.076)		
ref	0.042**(0.038)	0.030(0.209)	0.031(0.175)		
mfa	0.009(0.534)	0.005(0.790)	-0.003(0.832)		
secur			0.005(0.911)		
quota	0.0001(0.674)	-0.001(0.250)			
customs		0.060(0.157)			
Year Dummies	Yes	Yes	Yes	No	Yes
Group Dummies	No	No	Yes	No	No
cons	-0.354(0.300)	0.141(0.707)	0.475(0.324)	0.153(0.470)	
Hansen's statistic	10.730(1.000)	18.590(1.000)	13.570(1.000)	19.760(1.000)	
AR(1)	-2.360**(0.018)	-2.380**(0.017)	-2.070**(0.038)	-1.700*(0.090)	91.6***(0.000)
AR(2)	-1.310(0.189)	-0.570(0.567)	-0.950(0.344)	-0.370(0.714)	

Note: *,** and *** denote significance at 10%, 5% and 1% Levels of Significance, respectively. Figures within parentheses are P-values.

Table 5: Capital-Constrained Model: State-wise Two-Digit Data.
Dependent Variable: $logn_{it}$

Variable	1	2	3	4
$logn_{it-1}$	0.599***(0)	0.577***(0)	0.717***(0.010)	0.238*(0.086)
$logn_{it-2}$	0.299***(0.001)	0.265***(0.067)	0.145(0.193)	0.167**(0.036)
$logw_{it}$	-0.182***(0.012)	-0.214***(0.005)	-0.210***(0.002)	-0.093***(0.002)
$logw_{it-1}$	0.189***(0)	0.167***(0.004)	0.209***(0.002)	0.050*(0.093)
$logw_{it-2}$	0.0465(0.521)	0.032(0.714)	-0.038(0.526)	0.022*** (0.022)
$logk_{it}$	0.218***(0.01)	0.176** (0.027)	0.249***(0.001)	0.049*** (0.002)
$logk_{it-1}$	-0.1133(0.267)	-0.081(0.426)	-0.115(0.118)	-0.030(0.113)
$logk_{it-2}$	-0.0634(0.391)	-0.021(0.698)	-0.034(0.565)	0.002(0.907)
$dlogy_{it}$	0.282(0.1o8)	0.402***(0.002)	0.316***(0.007)	-0.012(0.507)
$dlogy_{it-1}$	0.06* (0.066)	0.236(0.116)	0.087(0.227)	-0.007(0.625)
$dlogy_{it-2}$	0.034* (0.062)	0.104 (0.129)	0.079(0.142)	0.004(0.828)
$logh_{it}$				0.389***(0)
$logh_{it-1}$				-0.084*(0.096)
$logh_{it-2}$				-0.060***(0.065)
util	0.0243 (0.766)		0.012(0.857)	
polln	-0.033(0.138)		-0.029*(0.090)	
envreg	0.002(0.897)	0.0002(0.996)		
labreg	-0.120*(0.069)			
ref		0.039(0.112)	0.025*(0.096)	
mfa	0.0199(0.275)	0.039**(0.019)		
quota		0.003**(0.043)		
customs		-0.124*(0.098)		-0.105(0.295)
Year Dummies	No	Yes	No	No
Sector Dummies	No	No	Yes	No
State Dummies	No	No	No	No
cons	0.4946 (0.116)	-0.0111(0.943)	0.088(0.713)	-0.358***(0.003)
Hansen's statistic	33 (0.992)	32.87 (0.992)	30.12 (0.998)	28.99(1)
AR(1)	-2.36** (0.018)	-2.26** (0.024)	-2.53** (0.011)	-3.01*** (0.004)
AR(2)	-1.29 (0.198)	-1.13 (0.26)	-1.59 (0.112)	-0.81(0.417)

Note: *,** and *** denote significance at 10%, 5% and 1% Levels of Significance, respectively. Figures within parentheses are p-values.

Table 6: Output-Constrained model: State-wise Two-Digit Data.
Dependent Variable: $logn_{it}$

Variable	1	2	3	4
$logn_{it-1}$	0.240**(0.012)	0.173(0.142)	0.176(0.192)	0.566***(0.000)
$logn_{it-2}$	0.197***(0.002)	0.153*(0.08)	0.261*(0.09)	0.272***(0.009)
$logw_{it}$	-0.081***(0.001)	-0.077***(0.001)	-0.104***(0.003)	-0.112(0.147)
$logw_{it-1}$	0.046*(0.052)	0.037*(0.085)	0.042(0.158)	0.181***(0.000)
$logw_{it-2}$	0.031***(0.000)	0.023*(0.055)	0.034*(0.092)	0.036(0.538)
$logy_{it}$	0.011(0.584)	-0.004(0.784)	-0.017(0.461)	0.389***(0.000)
$logy_{it-1}$				
$logy_{it-2}$	0.007(0.79)	0.016(0.315)	0.033(0.184)	-0.328***(0.000)
$dlogy_{it}$	-0.002(0.952)	-0.003(0.898)	0.03(0.247)	
$dlogy_{it-1}$				-0.219*(0.059)
$dlogy_{it-2}$	0.01(0.319)	0.01(0.469)	0.01(0.465)	0.055(0.333)
$logh_{it}$	0.394***(0)	0.405***(0)	0.399***(0)	
$logh_{it-1}$	-0.093**(0.013)	-0.066(0.143)	-0.067(0.195)	
$logh_{it-2}$	-0.073***(0.008)	-0.058*(0.088)	-0.098(0.102)	
util	-0.007(0.529)	-0.014(0.189)		
mfa			0.016*(0.032)	0.051***(0.001)
polln1			0.011(0.157)	-0.051**(0.015)
envreg1			0.001(0.937)	-0.005(0.770)
labreg	-0.02*(0.081)	-0.008(0.606)		-0.164**(0.013)
ref			0.016***(0.028)	
quota		0.0002*(0.078)		0.000(0.410)
customs	-0.021**(0.028)			-0.062(0.122)
Year Dummies	No	No	Yes	Yes
Sector Dummies	No	Yes	No	No
cons	-0.244**(0.035)	-0.405***(0.004)	-0.386***(0.012)	0.898**(0.016)
Hansen's statistic	22.86(1)	22.74(1)	9.800(1)	32.88(0.99)
AR(1)	-3.36***(0.001)	-2.94***(0.003)	-2.49**(0.013)	-2.46**(0.014)
AR(2)	-0.81(0.419)	-0.63(0.526)	-0.98(0.329)	-1.36(0.174)

Note: *,** and *** denote significance at 10%, 5% and 1% Levels of Significance, respectively. Figures within parentheses are p-values.

Table 7: Average Estimates of the Long-run Elasticities (LRE) of Employment with respect to Different Variables

LRE of Employment with respect to:	**Estimate based on CCEM**	**Estimate based on OCEM**
Wages	-0.609*(-1.725)	-0.410***(-2.831)
Capital	0.866***(6.272)	
Demand Shock	1.040***(3.470)	0.928***(7.953)
Output		0.777***(5.561)
Manhours	-0.026(-0.166)	-0.056(-0.853)
Adjustment Speed	**1.633***(14.952)**	**2.478***(6.171)**

Note: *,** and *** denote significance at 10%, 5% and 1% Levels of Significance, respectively. Figures within parentheses are t-statistics.

Table 8: Contribution of major variables to the average annual growth rate of employment based on long-run elasticities

Model	Explained Rate by , W, H & K or Y	Explained Rate by K	Explained Rate by W	Explained Rate by H	Explained Rate by Y	Actual Growth Rate of N	Explained Rate by other variables
CCEM	0.497	7.023	-6.504	-0.022		-5.167	-5.664
OCEM	-0.277		-4.379	-0.048	4.149	-5.167	-4.890

Table 9: Alternate models with All-India Three-Digit data using lockouts and unrest (1984-85 - 1997-98).
Dependent variable: $logn_{it}$

Variables	**1**	**2**	**3**	**4**
$logn_{it-1}$	0.599***(0.002)	0.718*(0.065)	0.487***(0.000)	0.367***(0.007)
$logn_{it-2}$	0.221(0.183)	0.084(0.849)	0.215(0.122)	0.396**(0.019)
$logw_{it}$	0.187(0.552)	-0.103(0.77)	0.088(0.746)	-0.084(0.741)
$logw_{it-1}$	0.201(0.243)	0.357(0.353)	-0.338(0.358)	-0.075(0.769)
$logw_{it-2}$	-0.262(0.463)	-0.391(0.17)	0.053(0.763)	
$logk_{it}$	0.120**(0.021)	0.297**(0.033)		
$logk_{it-1}$	-0.079(0.437)	-0.322*(0.071)		
$logk_{it-2}$	0.073(0.509)	0.194(0.117)		
$logy_{it}$				0.224***(0.005)
$logy_{it-1}$				
$logy_{it-2}$			0.288***(0.000)	
$dlogy_{it}$	0.415***(0.000)	0.275(0.156)	0.616***(0.000)	0.410***(0.000)
$dlogy_{it-1}$	0.123(0.411)	0.093(0.762)	0.386***(0.000)	0.245**(0.043)
$dlogy_{it-2}$	0.008(0.919)	-0.011(0.845)	0.012(0.745)	
$logh_{it}$		0.01532(0.899)		-0.066(0.343)
$logh_{it-1}$		0.058(0.693)		0.054(0.407)
$logh_{it-2}$		-0.09(0.476)		
customs	-0.00241(0.985)		-0.124(0.262)	
polln	-0.033(0.387)			
lib1	0.013(0.562)			
mfa	0.034(0.284)			
envreglat	-0.002(0.945)			
quota		0.001(0.755)	0.002(0.184)	
lockout	0.013*(0.056)	0.025**(0.013)	0.017**(0.027)	0.014**(0.039)
unrest	-0.002**(0.028)	-0.004*(0.051)	-0.002*(0.058)	-0.001**(0.047)
cons	0.769*(0.099)	0.377(0.329)	0.283(0.141)	0.362(0.135)
Hansen's Test Statistic	18.64(1)	10.73(1)	17.15(1)	20.52(1)
AR(1)	-2.35**(0.019)	-1.79*(0.073)	-2.33**(0.02)	-1.9*(0.057)
AR(2)	0.12(0.904)	0.41(0.681)	0.31(0.754)	-0.58(0.561)

Note: *,** and *** denote significance at 10%, 5% and 1% Levels of Significance, respectively. Figures within parentheses are p-values.