Cross-border environmental regulation and firm labor demand*

Pavel Chakraborty† Anindya S. Chakrabarti‡ Chirantan Chatterjee§

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Abstract

In 1994, due to environmental concerns, Germany banned a chemical called 'Azo-dyes', a primary input for the leather and textiles firms in India (a key exporter). Exploiting this as a quasi-natural experiment, we examine the effects of this cross-border regulatory change on labor compensation, particularly managerial, for both Indian upstream (dye-producing) and downstream (leather and textile) firms. We find that the regulation increased compensation of managers by 1.3–18% in dye-producing firms compared to other chemical firms. This is due to the combination of changes such as investing in R&D, product churning, import of high-quality intermediates, due to the ban, which led to this change in within-firm labor composition. This increase in overall compensation is driven only by fixed component (wages), consistent with the effects of a long-run shock. We find no such effects for downstream firms. We believe, our study is one of the first to show that just like tariff, non-tariff barriers (NTBs) can also significantly affect within-firm labor composition.

Keywords: 'Azo-dyes', Non-tariff barriers, Cross-border Environmental Regulation, Managerial Compensation, Dye-producing Firms, Upstream and Downstream Sectors

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†Department of Economics, Management School, Lancaster University, UK; Email: p.chakraborty1@lancaster.ac.uk

‡Economics Area, Indian Institute of Management, Ahmedabad, India; Email: anindyac@iima.ac.in

§Science Policy Research Unit (SPRU), Business School, University of Sussex, UK & Visiting Fellow, Hoover Institution, Stanford University & Visiting Faculty, Indian Institute of Management, Ahmedabad; Email: c.chatterjee@sussex.ac.uk

1 Introduction

Understanding the effects of cross-border regulations on labor demand is increasingly becoming important given the continuous drop in tariffs (after the 1988 Uruguay Round negotiations) and rise in non-tariffs barriers consequently. While there is a vast array of literature on the effects of various forms of trade reforms (import competition, tariff drop, Free Trade Agreements (FTAs), etc.) on labor market adjustments (Revenga (1992); Artuc et al. (2010); Autor et al. (2013); Dix-Carneiro (2014); Chakraborty and Raveh (2018)), there is a dearth of evidence (both theoretical and empirical) on the effects of non-tariff barriers (NTBs, hereafter) despite the growing prevalence of NTBs in international trade.

For example, a 2002 study by the International Trade Commission (ITC) found that 40% of exports are subject to NTBs (UNCTAD, 2005). Recent technical reports by WTO (2012) and De Melo and Nicita (2018) also highlight that in the last few decades, use of NTBs has increased to support a wide range of development strategies, domestic priorities, policy objectives (including SDGs), etc.[1]

Can a cross-border environmental regulation (or a NTB) influence labor choices within a firm? Environmental regulations (both domestic and foreign) often spur innovation (Jaffe and Palmer (1997); Chakraborty and Chatterjee (2017)) and adoption of new technology (Gray and Shadbegian (1998); Popp (2002); Aghion et al. (2016)) which, in turn, may lead to changes in production technologies and product portfolios at the firm level. Such changes require labor adjustments in terms of conceptualizing as well as undertaking research for new substitute inputs/products. Previous research on environmental regulations have shown sufficient evidence on firms adapting new strategies to comply with these regulations that has important implications for productivity (Gollop and Roberts (1983); Berman and Bui (001a)) and competitiveness (Lanoie et al. (2011); Rexhäuser and Rammer (2014)). However, there is a prominent gap in documenting and understanding the potential effects of such regulations on demand for managing such re-organizations (in terms of changes in the production process) within a firm.

[1] This issue has become increasingly important as environmental and health-related standards have become binding constraints to the imposition of such barriers (Chaturvedi and Nagpal (2002); Fontagné and Orefice (2018)).

The question of cross-border effects of regulatory changes on managerial inputs becomes even more important from the perspective of the extant literature on firms' managerial practices, quality improvements, and organizational structure, and the corresponding implications for overall performance. For example, Bloom et al. (2013) show that differences in managerial practices can explain a substantial part of firm level productivity across Indian textile firms.[2]

Adopting a quasi-natural experiment, in the form of a foreign regulatory change, in the context of India we study the effects of a NTB on managerial demand and compensation. To the best of our knowledge, our study constitutes one of the first to explore the effects of NTBs on such dimensions.

In July 1994, Germany banned a widely-used chemical dye known as "Azo-dyes" based on a petition filed by a consumer advocacy group due to health and environmental concerns.[3] The ban primarily targeted any leather and textile product that is treated with Azo-dyes. Banning of this input (which is one of the oldest and widely used chemicals in the production of leather and textile goods) for downstream (or leather and textile) firms became a *de-facto* ban for the producers of this particular input in India, i.e., the dye-producing firms within the Indian chemical industry.[4] Utilizing a rich data set of Indian manufacturing firms that uniquely distinguishes between the compensation of managers and non-managers,[5] we explore the impact of this plausibly exogenous environmental regulation on the demand for managers in the upstream dye-producing and downstream leather and textile firms. This allows us to trace out the spillover effects of a cross-border regulation in terms of firms' labor demand through integrated global supply chain.

The emphasis on the upstream industry and their labor adjustments (in terms of demand

[2]They ran a field experiment on large Indian textile firms by offering them management consultancies; adoption of these management practices raised productivity 17% through improved quality and efficiency.

[3]Details of the regulation and its merits in the context of our case are outlined separately in Section 2.

[4]Germany was one of the largest consumers of Indian textile products, with textiles alone making up about 76% of all consumer goods imports in 1994 (Iyer (1992); Industriebank (1994)). On the other hand, the Indian textile sector accounts for some 70% of the consumption of dye-stuffs produced by the chemical sector. (Source: https://www.dnb.co.in/Chemical/overview.asp)

[5]We define managers as any workers who manage at least one other worker or who is the sole worker in the firm. The rest of the workers are defined as non-managers. Such definitions are standard in the literature (see, for example, Chakraborty and Raveh (2018)). In Section 4, we will discuss the definition and the background in detail.

for managers), is central to our analysis. The ban on Azo-dyes was an irreversible regulatory change and therefore could potentially drive significant changes in terms of designing new product portfolios (e.g., changing their core product) and/or engage in research to innovate a new formidable substitute, altering the demand for managers as well as non-managers. As Garicano (2000) and Caliendo and Rossi-Hansberg (2012) argue, firms that need to solve new problems in terms of their production may need to upgrade the skills of the workers (or non-managers), while simultaneously reduce the cost of production by increasing the quality and number of managers who specialize in solving problems as well as in innovating. Hence, our empirical approach requires an examination of the effect of complementarity (or substitutability) arising out of the regulatory changes (which constitutes a product ban for the dye-makers) on the demand for managers relative to the demand for non-managers.

We start by presenting some descriptive evidence linking the cross-border regulatory change and the relative demand for managers in our sample of Indian chemical firms for the period of 1989–2002. **Panel A** of **Figure 1** shows the managerial compensation as a share of total compensation for dye-producing firms (which are primarily affected by the regulation, therefore our treated group) and firms which produces other types of chemicals (our control group). The figure clearly shows that while there is no difference in the pre-ban period (in the period 1989–1993), there is a wide gap in the post-ban timeframe. **Panel B** of **Figure 1** does the same, but for R&D expenditure of those firms. We see a similar picture here: no difference in the trends before the ban, but quite substantial change in the post-ban period.

We calculate a simple correlation between managerial compensation and R&D expenditure for dye-producing and other chemical firms. In the case of the former, the correlation coefficient is 0.76, whereas for the latter the same is 0.05. **Panels A** and **B** of **Figure 1** points toward a possible causal effect of the mentioned NTB on managerial compensation through a surge in R&D expenditure.[6]

The key point in exploiting this particular event for causal inference is that the ban on

[6] Aghion et al. (2019) show that firms that are more R&D intensive pay higher wages on average. They use a matched employee-employer dataset from the UK to quantify the wage premium of innovative firms. They complement the empirical analysis with a theoretical model to capture the idea that innovativeness can be reflected in the degree of complementarity between workers in low-skill and high-skilled occupations.

Azo-dyes provides a plausible exogenous change in industry level dynamics, in our case for dye-producing firms (representing the 'treatment' group) relative to the rest of the chemical firms (representing the 'control' group). Using a difference-in-differences approach, we find a remarkably persistent and economically meaningful positive effect. In particular, our main finding is that the ban led to a significant increase in demand for managerial workers; around 2.2–18% increase in the compensation of managers in dye-producing firms compared to other chemical firms. In terms of the share, it increased by about 1.3% for the dye-producing firms. Our benchmark finding is robust to all possible simultaneous events, such as drop in tariffs due to 1990s trade reforms, import of finished goods, raw materials, export growth, etc., different specifications, and alternate estimation techniques. Specifically, we rule out any industry- or firm-specific trends as causing the effect, such as a drop in input tariffs (Chakraborty and Raveh, 2018).

Examining the mechanisms which led to this observed increase in managerial compensation, we find that the ban forced the dye-producers to develop a new core product, improved and safe substitute to Azo-dyes. Now, developing a new core product or changing product portfolio requires conceptualization/ideas, R&D expenditure, new imported raw materials, creating sales partnerships, doing business development, among others.[7] All these changes (in the production processes of a firm) could potentially create a new set of non-routine problems. And, in order to solve for them, a representative firm needs higher inputs from managers (relative to non-managers) that can solve these, and plan for the future, among other tasks. Combined, the value of the managers (both price and number) would increase significantly, which is what we find in our analyses.[8] These patterns are primarily driven by the domestic private Indian firms producing intermediate goods (by end use) and firms' across the size distribution except for the firms below the 25th percentile.

[7] Aggarwal et al. (2020) show that it is the across-team rather than within-team knowledge diversity, which helps a firm to innovate. Such kind of phenomena have also been highlighted by Teece (1996). He argues that innovation would require a whole range of activities that are intensive in managerial talent: research, conceptualization and development of new products, branding and marketing the product, and so on.

[8] We also find significant changes in the extensive margin, i.e. in the number of managers. We note that PROWESS is not suitable to study the extensive margin of labor demand as it provides very limited data on the number of employees. Therefore, given the data limitations, we do not claim for a straight generalization of our results for out of sample firms in India. But, the analysis has the benefit of giving us a rough idea about the effects at the extensive margin of firms' demand for managers.

Digging deeper, we decompose the total managers' compensation into its wages (fixed component) and incentives (variable component). We find that it is only the fixed component that increases as a response to the ban. This is consistent with the idea or literature by Ederer and Manso (2013) which argues that in response to long-term or permanent shock, it is the wage and not 'pay-for-performance' (or incentive) component that turns out to be important. All these changes for a dye-producing firm in the one hand led to decline in the profits, but increase in productivity on the other. Finally, we show that none of these effects (in terms of changes in the product portfolio or R&D expenses or increase in the value of managers, etc.) hold for downstream firms (which we use as a placebo/counterfactual).

We end our analysis by summarizing the main findings and discussing their implications in order to understand the impact of such kind of regulation in terms of technical change (Acemoglu, 2002). In particular, we interpret the main findings to be an outcome of changes in firms' organization of knowledge (product portfolio and innovation), triggered by the NTB/regulation. Broadly, our evidence suggests that a firm may value managers more relative to non-managers if they face such kind of NTB, essentially because that may motivate a manager to innovate, reorganize tasks (in terms of changing their core versus non-core product portfolio), etc. This is our primary contribution.

This paper relates primarily to three different strands of literature. First and foremost, our main mechanism works through documenting the regulatory impacts of firm behavior. There is an overwhelmingly large volume of literature concerning non-tariff measures, both TBTs (Technical Barriers to Trade) and SPS (Sanitary and Phytosanitary), and its effect on different firm level attributes: (1) trade (especially exports) (Chen et al. (2008); Fontagné et al. (2015); Chakraborty (2017); Fontagné and Orefice (2018)), (2) firm exit (Biorn et al., 1998), (3) innovation (R&D expenditure, patents) (Jaffe and Palmer (1997); Berman and Bui (001a); Ambec et al. (2013)), (4) technical change (Calel and Dechezleprêtre, 2016), (5) productivity (Perkins and Neumayer, 2012), (6) capital employed (Gray and Shadbegian (1998), Nelson et al. (1993)), (7) plant or establishment birth and size (Dean et al., 2000), (8) input reallocation (Vandenbussche and Viegelahn, 2018), (9) markups (Singh and Chanda, 2021), etc.

Overall, the evidence is mixed. Our paper deviates from this literature and looks at the effect of a foreign environmental regulation on the composition of labor within a firm. To the best of our knowledge, this is the first study that focuses on a NTB or cross-border environmental regulation (which is exogenous in nature) and examine changes in labor demand within and between firms. Our study complements Navaretti et al. (2020)[9] and adds to this nascent literature by showing similar effects for Indian dye-producing firms but in response to a ban which was primarily directed to their downstream industries.[10]

Second, the study also contributes to the overall literature on environmental regulations. Theoretically, the effect of environmental regulation on employment is uncertain (Bovenberg and van der Ploeg (1996); Carraro et al. (1996); Schneider (1997)). On the one hand, environmental regulations could increase the costs of production through the use of new products and processes thereby reducing profits and labor demand. On the other, improving the production processes and using new technologies (to reduce environmental costs) would require labor input and that may promote employment.

Empirically, there exists a small literature which studies the employment effects of environmental regulations (Goodstein (1995); Berman and Bui (001b); Cole and Elliott (2007); Greenstone (2002); Walker (2013); Gray et al. (2014); Liu et al. (2017)).[11] However, all of these studies (i) overall employment changes (either at the national, regional, or plant level) rather than changes in worker composition within a firm, and (ii) exploit domestic regulation(s) which may be endogenous to the performance of firms. We, on the other

[9]They use a French employer-employee data set to investigate the impact of TBTs on the organizational structure of firms. They show that TBTs do influence the labor composition of firms. However, the study does not put forward any mechanism as to what is the channel through which TBTs increase the value for managers in those exporting firms. In contrast, we show that the change in the product portfolio and innovation channel raises the value for managers relative to non-managers. Additionally, we also show that the effect of the regulation affects both the intensive and extensive margin unlike Navaretti et al. (2020), which only looks at the extensive margin or the employment effects.

[10]The study can also be placed in the larger context of various tariff-related factors impacting the labor market via trade (Goldberg and Pavcnik (2003); Amiti and Cameron (2012); Ahsan and Mitra (2014); Chakraborty and Raveh (2018); McCaig and Pavcnik (2018)).

[11]The evidence is again, mixed. Greenstone (2002) show that in the first 15 years of implementation of the "Clean Air Act", 590,000 jobs were lost in pollution-intensive industries along with significant reduction of the capital stock. More recently, Gray et al. (2014) argue the opposite while assessing the effect of the Environmental Protection Agency (EPA) regulations on the labor demand for the pulp and paper industry in the US. They argue that investment in pollution reduction equipment and technologies led to higher labor employment. In a slightly different context, Archsmith et al. (2018) show that short-term exposure to air pollution significantly affects the work performance of a group of highly skilled, quality-focused employees.

hand, use a cross-border regulation and look at within-firm demand for managerial workers (relative to non-managerial workers).

Our study highlights one crucial point: organizations need to manage innovations and other auxiliary activities while simultaneously adapting to new developments in the market (Dessein and Santos (2006); Alonso et al. (2015)) in the form of regulation or otherwise. Since "management matters" to quote Alexopoulos and Tombe (2012),[12] this activity is generally correlated with changes in the compensation structure of the managers. The interaction between technological change, management and resulting inequality is well-recognized in the literature (Galor and Moav (2000); Garicano and Rossi-Hansberg (2004); Gabaix and Landier (2008); Berrone and Gomez-Mejia (2009)).[13]

Finally, we note that there is nascent literature on understanding policy transmission through input-output network (Liu, 2019). This is different from propagation of macroeconomic shocks (e.g. as described in Baqaee and Farhi (2019)) and technology diffusion (Acemoglu et al. (2016); Basker and Simcoe (2017)). A parallel literature also deals with how competition and regulatory frictions in the product market interact with the propensity to innovate and contributes to the transmission of innovation (Nelson et al. (1993); Millimet et al. (2009); Sanyal and Ghosh (2013); Eizenberg (2014); Beraja et al. (2020)).[14] This literature is new and Liu (2019) provides some early empirical evidence of such transmission. Our paper contributes to this literature by providing a clean identification of a policy shock across upstream and downstream producers.[15]

The rest of the paper is structured as follows. Section 2 provides a brief institutional background of the regulation. We describe the dataset we use and documents some first-cut

[12]See also Beaudry and Francois (2010) for manager's role in technology adoption.

[13]Given the interaction between the nature of technology and path-dependence of the resulting economic growth which in turn influences technology choice, our paper also provides a glimpse of technological shift and sharp changes in inequality on a narrow scale. From a growth theoretic perspective, a large literature recognizes the interplay of competition, directed technological change, wage inequality and growth in aggregate income (Acemoglu (1998, 2002); Aghion et al. (2005, 1997)). Acemoglu et al. (2014) brought in the effect of environmental changes on technology choice and economic growth from a long-run perspective.

[14]Shocks in the form of regulations often spur innovation (Jaffe and Palmer (1997); Blind (2012); Dechezleprêtre and Glachant (2014); Dechezleprêtre et al. (2015); Aragon-Correa et al. (2020)), an idea that owes its origin to the so-called Porter's hypothesis (see, for example, Ambec et al. (2013) for a review on the debate).

[15]Our results are consistent with Liu (2019) in that the main effect is seen in the upstream and not downstream firms. More on this in Section 6.

evidences of our findings in Section 3. Section 4 explains the empirical strategy and deals with the concerns related to the endogeneity of the ban. Section 5 describes our benchmark results, the mechanism(s) behind them, and effects on overall firm performance. We also examine what happened to the downstream firms in Section 6. Lastly, we discuss our findings and implications in Section 7.

2 Institutional background

Since the 1990s, a number of European countries such as Germany, Finland, Switzerland, Sweden, Austria, etc. have put forward higher requirements for human health and environmental protection. This is especially true in case of the leather and textile goods. Following strict environmental protection regulations, textile associations in these countries put forward "Environment-friendly Textile" (Eco-Textile), that is textiles with "Environmental Labels" which tests for the presence of hazardous substances. Products with "environmental labels" which passed the tests, were also welcomed by people since they did not cause any harm to human health and the environment. In this regard, a lab report on "Azo-dyes" showed that the prolonged contact of this dye with human skin could be fatal as these dyes can undergo a reaction, eventually causing cancer (Chung, 2000).

The environmental implications of the dyes are also significant. The use of Azo-dyes involves high volume of water in the dyeing process. And, when a Azo-dye is used in the process, a portion of the dyes remains in the water. As a consequence, high volumes of waste waters containing dyes and related auxiliaries are produced. The conventional treatments are also not efficient in the removal or biological degradation of these dyes.[16] Therefore, the dyes could still be present in the final effluent or in the sludge of the treatment plant when released into the environment (Ribeiro and Umbuzeiro, 2014).

Based on these implications (on both human and environmental health), a petition was filed by a consumer advocacy group in the German Supreme Court. And, in July 1994 the German government adopted a legislation to prohibit the production, use, and sale of

[16] Chung (2000) highlights that Azo-dyes are regarded as relatively persistent pollutants because they are not readily degraded under aerobic conditions.

Azo-dyes. This ban was followed by similar legislation across other European countries such as Netherlands, Austria, France, Norway and finally adopted by the European Union (EU). The Indian government also issued a similar legislation in 1997 to completely stop the production and sale of Azo-dyes even in the domestic market. The effect of the ban continues even to date to the extent of the absence of Azo-dyes becoming an essential part of quality control in the international trade of textiles.

According to a OECD (Organisation for Economic Co-operation and Development) report (OECD, 2006), India was the most affected country by this ban. Multiple factors were involved: (a) India was a large producer of dyes along with one of the largest exporters of leather and textile goods in the global market; (b) a relatively large fraction of Indian leather and textile firms depended heavily on Azo-dyes. Tewari and Pillai (2005) point out these firms exported about 25–70% of the products treated with Azo-dyes to the European Union, with Germany as one of its main destinations. A holistic ban on a crucial input for leather and textile firms incentivized vigorous innovation by the Indian dye-producers to try to produce similar alternatives that are cost-effective (Pillai, 2000). They also offered credit and technical assistance to their main customers which are the Indian textile and leather firms to adopt their new products. All of these changes in activities (production and sales of the new alternatives) may have significantly influenced the demand for managers in a dye-producing firm rather than other chemical firms.

3 Dataset and some stylized facts

This section outlines (a) the dataset we use and its unique features and key components, (b) some stylized facts to motivate and support our main research question.

3.1 Firm level data: PROWESS

Our source of firm and firm-product level data is the PROWESS database, maintained and published by the Centre for Monitoring Indian Economy (CMIE). The database contains information (obtained primarily from income statements and balance sheets) on a large number of publicly listed companies. These firms are predominantly private Indian firms or affiliated to private business groups. There is a small fraction of firms which are either government or foreign-owned. Since the companies are publicly listed, the fraction of small companies is rather limited. The source of data for large companies is their balance sheets, whereas, for small companies, CMIE conducts periodic surveys. The unorganized sector has no presence in the database.

This dataset is unique in terms of its coverage – especially in the 1990s. There are alternative sources like the Indian Annual Survey of Industries (ASI), but ASI has some crucial limitations, at least in our present context. Below we list the advantages of using the PROWESS database.

First and most importantly, PROWESS keeps track of firms over each year making it a panel format. Even though some might argue that ASI might be more suitable to explore labor market changes, but it only reports a repeated cross-section till 1997 which limits the scope substantially; the panel version starts from 1998 onward. The changes that we plan to identify are within-firm effects, which may not be possible with repeated cross-section data.

Second, the PROWESS sample covers companies across 310 manufacturing industries (with separate 5-digit National Industrial Classification (NIC) 2008) that belong to 22 (2-digit NIC code 2008) aggregated industries over the period of 1989–2002. In this paper, we focus on the 'Chemical' industry ('20' at the 2-digit level as per NIC 2008). However, for our analysis, we go deep and identify the 'dye-producing' chemical firms at the 5-digit level of NIC 2008. The ASI does not allow us to identify firms at the 5-digit level thirty years prior and this is crucial to our identification strategy. According to the classification, a dye-producing firm is represented by "*20114 (5-digit NIC 2008) – Manufacture of dyes and pigments from any source in basic form or as concentrate.*" This is our treated group of firms and we use the rest, i.e., chemical firms excluding the dye-producing ones, as the control group. This is similar to Chakraborty and Chatterjee (2017).

Third, another crucial feature of the dataset which we utilize as our key dependent variable, is that it dis-aggregates compensation data by managers and non-managers.[17] The non-managers are defined as those who do not manage other employees, such as production workers, clerks, operators, etc. The total compensation data is further disaggregated into wages and bonuses, which helps us to identify the compositional effect.

Fourth, a key mechanism that we highlight in the paper in terms of explaining the changes in managerial compensation, after the ban (i.e., 1994), is the technology adoption or R&D expenditure of a firm. One of our main arguments in the paper is that the ban on one of the important outputs (during the 1990s) of chemical firms, Azo-dyes, induces them to engage in higher R&D to produce new products and this required managers for business development activities to reap benefits from the regulation. PROWESS reports detailed information on technology absorption which is also absent in ASI. The information on technology adoption, divided into R&D expenditure and royalty payment on technical knowhow (i.e., technology transfer), is mandatory as per section 217 of the Companies Act. As per section 217(1)(e), the information shall be attached to every balance sheet laid before a firm in the Annual General Meeting, in a report by its board of directors. We aggregate the expenditures on R&D and technology transfer, to represent the total innovation expenditure for any given firm.

Lastly, a unique feature of the PROWESS database is that it captures detailed information on quantity sold, sales, and capacity of each product manufactured by a firm. The 1956 Companies Act requires the firms to report detailed production data for all products manufactured by them. The products in our data set thus should be seen as narrowly defined categories within industries rather than a specific product variety like barcode scanner datasets.[18] There are over 4,000 unique products in our sample. These product codes were then mapped on to the NIC 2008 5-digit level industries. We also use information on the core product of a firm, its sales share, and whether a new product being introduced and/or

[17]We note that there is some scope for subjective interpretation of this terminology. However, none of that affects our analysis since we consider the aggregate managerial compensation. In addition, it would have been ideal if we could identify the R&D managers (such as scientists, etc.) versus non-R&D managers, but Indian data (without employer-employee information) unlike some Scandinavian economies limit us from examining that.

[18]Goldberg et al. (2010) provide a detailed description of the product classification in PROWESS as well as quality checks on the data.

dropped by a firm in order to understand the effects of the ban on product churning. We do it for both upstream and downstream firms.

We have about 350 firms in our dataset that belongs to the chemical sector, out of which about one-third corresponds to the dye-producing sector. The coverage of the PROWESS database is quite extensive in terms of economic activities (more than 70%) in the organized industrial sector. These firms are also responsible for 75% (95%) of corporate (excise duty) taxes collected by the Indian Government (Goldberg et al., 2010). Additionally, the dataset also provides information on a variety of firm level characteristics inclusive of, but not limited to, total sales, exports, imports, cost, production factors employed, expenditure, gross value added and assets among others. All nominal values are represented in Millions of Indian Rupees (INR) deflated with respect to the industry-specific Wholesale Price Index (WPI) with the base year as 2005. The details are given in **Appendix A**. **Table B1 (Appendix B)** presents summary statistics of all the variables used. We use an unbalanced panel of firms for the time period 1989–2002.

3.2 Unconditional moments of pre– and post–ban

We start by looking at the association between labor compensation, in our case managerial compensation, and innovation expenditure of a firm. We compute simple correlations between managerial compensation and R&D expenditures along with technology transfer in **Table 1**.

Column (1) reports for R&D, while column (2) does it for technology transfer. We find that the correlation is positive and significant at 5% level for firms across both the control and the treatment group in the upstream and downstream sectors. However, the magnitude of the correlation for the treatment group in the upstream firms is much larger than the others (0.63 as opposed to 0.05, 0.18 and 0.19). The correlation with technology transfer on the other hand, is clearly negligible both in magnitude as well as significance (especially for upstream firms). Next, in columns (3) and (4) we divide the correlation between R&D expenditure and managerial compensation over two periods: pre– and post–ban. We find that for the dye-producing firms the correlation coefficient increases substantially from 0.42

to 0.71; such an increase is absent for any other group of firms.[19]

Next, we show that the above correlation between managerial compensation and R&D expenditure is systematic. The idea is that if the ban did not induce any changes in the innovative activities of the downstream sector, we should not see any simultaneous changes in managerial compensation as well. **Figure 2** shows such is the case. We do not find any difference in the R&D expenditure (**Panel B**) of the leather and textile firms with respect to other manufacturing (less chemical), especially after 1994. If that is true, then we should not get any evidence of systematic divergence of the share of managerial compensation for the leather and textile firms when compared to other manufacturing sectors after 1994; **Panel A** shows what we expect.[20] The difference between these two plots is what we aim to establish in terms of the causal effect of the ban on the managerial compensation through our empirical analysis.

These findings seem to indicate two important implications. First, the ban seemed to have a significant impact on the compensation structure for the dye-producing firms, but not much of an effect on the firms which produce other types of chemicals or are downstream (Leather & Textile and Other Manufacturing). Secondly, the mechanism for such an increase in the managerial compensation can potentially be found through how the firms responded via innovation activities, in particular, through R&D related activities. Clearly, these inferences are based on plain correlations (as we do not control for a host of other observable and unobservable characteristics) and therefore, cannot be interpreted as a causal mechanism. Below, we test for these findings along with their plausible mechanisms in an explicitly causal framework.

[19]We also look at the average values of innovation expenditure (and its components) and managerial compensation in the pre- and post-ban (Azo-dyes) in **Table B2 (Appendix B)**. We focus on both upstream and downstream groups of firms. The numbers show that during the post-ban period, expenditures on innovation, R&D, and technology transfer increased sharply for both upstream and downstream firms. However, the effects on compensation are quite different. Only the managerial compensation for dye-producing firms (our treatment group) increased significantly in the post-ban period. Neither the non-managerial compensation for the focal group of firms nor did the compensation (both managerial and non-managerial) for the firms in the control group respond to the ban. The compensation (both managerial and non-managerial) of the downstream firms also does not show any response (only a slight increase in total compensation for firms in other manufacturing sectors (total manufacturing - chemical - leather and textile firms), but the increase is barely significant).

[20]The control group that we use here is the other manufacturing sectors excluding the chemical sector. Putting it differently, we use leather and textile firms as counterfactual or placebo. More on this in Section 6.

4 Empirical strategy: Cross-border spillover of environmental regulation on the labor market

In this section, we describe our empirical strategy of the effect of the Azo-dyes regulation from Germany on Indian dye manufacturers using a reduced-form equation. Our study design utilizes a difference-in-differences framework over the period 1989–2002, where we designate the dye-producing firms as the treatment group and firms engaged in the production of other chemicals as the control group. The ban happened in 1994, indicating that the pre-ban period to be 1989–94 and the post-ban 1995–2002. We use the following specification:

$$\log(y_{ijt}) = \beta\,(Ban_{94} \times Dye_{ij}) \;+\; firmcontrols_{it} + \phi_i + \theta_{jt} + \epsilon_{ijt} \tag{1}$$

y_{ijt} represents our outcome variable of interest for firm i in sector j at time t. For our analysis, y is the managerial compensation of a firm i. Ban_{94} is a binary variable that takes the value of 1 in the post-treatment period, i.e., post-1994 years. The variable Dye_{ij} is a binary variable that takes a value of 1 if the i-th firm belongs to the dye-producing sector: if a firm belongs to "*20114 (5-digit NIC 2008) – Manufacture of dyes and pigments from any source in basic form or as concentrate.*"

We would like to note at this point that one may argue that this may not be the most ideal 'treatment' group that one could use. Ideally, we would want to identify the firms which are producing Azo-dyes and use them to represent the 'treatment' group. However, there is one major problem related to this: almost 80–85% of firms in our sample are multi-product firms. If we define the treatment dummy at the firm-product level, then for a large proportion of firms the same firm will be present in both of our treatment and control group, thereby completely contaminating the means of comparison across treatment and control group. And, our difference-in-difference estimates will be imprecisely estimated.

Additionally, it is still not too far fetched to identify the treatment and the control group at the firm and not firm-product level due to two reasons: (a) given the prevalence and wide-spread usage of Azo-dyes in the 1990s, one can safely assume that most of the dye-producing firms would produce Azo-dyes as one of their main or atleast one of the peripheral products; (b) the ban was a "Azo-dyes" ban not a general "Dye" ban related to production of leather and textile products. Therefore, given the ban the dye-makers would only stop producing Azo-dyes and not any other kind of dyes. It would have been much difficult to identify if the regulation was general in nature in terms of not naming or banning any particular dye.

However, the Azo-dyes ban is certainly not the only external shock that could influence the demand for managers for the dye-producing firms in India. There would be many other potentially exogenous events that would impact the firm level decision-making process including time-varying domestic macroeconomic factors. It is quite likely that many of such events would impact our estimates, especially the events happening around 1994. In order to potentially avoid this problem of identification, we include firms producing other types of chemicals during the same time-frame as the control group. The argument goes as follows: any event that is not chemical industry-specific (e.g., a domestic macroeconomic policy change), would impact both the dye-producing and other chemical producing firms in an identical fashion. Thus the net effects shown by the dye-producing firms in the post-treatment period over and above the firms in the control group (i.e., firms producing other chemicals in this context), would represent an effect attributable to a factor specific only to the dye-producing firms during the time of the ban.

Our coefficient of interest in Eqn. (1) is β. It measures the effect of the Azo-dyes regulation on managerial compensation for a dye-producing firm relative to other chemical firms. The underlying idea is that control group of firms potentially have the same characteristics as the treated firms, but they are not affected by the treatment. In summary, we expect that the demand for managers and hence, managerial compensation to rise due to undertaking of more activities related to product churning and R&D by the dye-producing firms.

$firmcontrols_{it}$ includes a vector of firm level characteristics, such as age, age-squared, assets (size of a firm), and technology adoption expenditure which can potentially affect the demand for managers. We also control for firm-specific time-invariant effects (ϕ_i) to control for other unobservable characteristics and industry-year fixed effects (θ_{jt}) to control for time-varying changes at the industry level, such as delicensing, drop in tariffs (input and output), etc.[21] We cluster our standard errors at the 5-digit NIC 2008 level.

However, the basic estimates still do not provide conclusive evidence of the causal effect because of the following three reasons: (a) omitted variable bias; (b) differential time trends; and (c) reverse causality. Below we will consider each of them separately and show that our results are robust to all three. We address the problem of omitted variables, by sequentially adding various firm and industry characteristics such as import of raw materials, import of finished goods, R&D expenditure, technology transfer, exports, input tariffs, etc. and their interaction terms with the treatment group, to our baseline specification. As for the latter ones, we first show that there were not pre-trends; secondly, there was no anticipation effect of the ban. Finally, we also show that managerial compensation or any other feature that is closely associated with the demand for managers did not influence the Azo-dyes ban through a series of explicit exogeneity checks in the following section.

4.1 Dealing with the endogeneity of the 'Azo-dyes' ban

We do a series of endogeneity checks in **Table 2**. We start by following Abramitzky and Lavy (2014) in column (1), where we show that our treatment (dye-producing firms) and control (other chemical firms) group were not on different time trends in the pre-ban period. We use pre-ban data from 1989 to 1993 to show there is no differential time trends in outcomes (in our case managerial compensation) for dye-producing and other chemical firms. Column (1) regresses managerial compensation on the interaction terms $Ban_t \times Dye_{ij}$ except that instead of choosing $t = 94$ (actual time of the ban), we use $t = 91$, 92, and

[21] Another major event during the same time period was that India joined the World Trade Organization (WTO) in 1995. Given such a major change in the trade-related policy, it is natural to expect that it can contaminate our estimates, say, due to exchange rate fluctuations. Other major macroeconomic effects could be seen via the unstable growth of the Indian economy after the 1991 financial reforms, along with volatile CPI inflation fluctuating between a wide range of approximately 3.8% (around 6.3% in 1994 and less than 4% in 2001) to around 14% (more than 13% in 1991 and 1998). We account for all such effects via the control group of firms (to account for aggregate effects that can affect all chemical-producing firms) as well as by controlling for time trends, industry-year fixed effects at various levels. All of our results are robust to different specifications.

93.

The estimates from column (1) suggest that there is no differential time trend in the managerial compensation for dye-producing and other chemical firms. Interpreting it differently, the idea here is to introduce some counterfactual bans to see if they had any impact on the managerial compensation. As our estimates show, we find limited evidence of any consistent impact of the counterfactual bans. If any, it shows an opposite or negative impact, but only for the year 1992 with no effect for the years 1991 and 1993. But, it would be difficult to establish a credible effect because it is based on observations of only two years (the data starts from 1989).

Secondly, one of the most obvious points here to note is that the ban originated in Germany and the destination was India. In 1989, Germany imposed a similar ban known as the PCP ban; it banned another popular chemical used by the leather and textile firms – pentachlorophenol (PCP). Although this ban was easily tackled as the substitute chemical was readily available in the market (Tewari and Pillai, 2005), this could set a precedence. Dye-producing firms could anticipate the Azo-dyes ban and can start adopting more technology and this can drive the managerial compensation of the dye-producing firms more than others.

Also, many of the dye-producing firms in India were multinationals. In particular, some of them have German and European origin. For example, BASF[22] is a major manufacturing firm specializing in chemical products, that continues to operate in India till date from 1967 with the present name.[23] Given the market presence of such multinationals who had headquarters within Germany (in Ludwigshafen in case of BASF), it is possible that the news of the Azo-dyes ban was not exogenous to them and therefore, their reactions in the Indian market would also pre-date the actual ban.

In addition, it could also be that the consumer sentiment had been growing against the use of Azo-dyes well before the imposition of the ban. Imagine there are two sets of firms: informed and uninformed in our category. The informed set of firms could know about

[22]Badische Anilin und Soda Fabrik; largest chemical producers in the world; see https://www.worldatlas.com/articles/which-are-the-world-s-largest-chemical-producing-companies.html

[23]See https://www.business-standard.com/company/basf-india-59/information/company-history.

these type of consumer sentiments (say, because of their distribution network) and start adjusting their product portfolio, and thus having an affect on the demand for managers pre-date to the actual ban. To see whether such events had any effect on the managerial compensation, we regress managerial compensation on the lagged years leading up to the ban. Column (2) shows no such responses. Thus, there does not seem to be any expectation in the market that could drive the changes in managerial compensation before the actual ban materialized.

Lastly, in columns (3) to (6) we follow Topalova and Khandelwal (2011) and regress our main variable of interest, $Ban_{94} \times Dye_{ij}$, on our main outcome of interest managerial compensation and other variables related to production viz. capital employed, total factor productivity (TFP) and skill intensity. In effect, we run the following specification:[24]

$$(Ban_{94} \times Dye_{ij}) = \pi \ X_{ijt-1} + \phi_i + \theta_{jt} + \ firmcontrols_{it} + \epsilon_{ijt} \tag{2}$$

In this case, θ_{jt} either represents industry-year fixed effects or the interaction of industry fixed effects with year trends. And, X_{ijt-1} is a vector of characteristics that can possibly influence the ban at either firm i or industry j level. It includes a share of managerial compensation (a larger share of managers may lobby for the ban in order to reap higher gains as evidenced), capital intensive and productivity[25] (this captures whether more capital intensive or productive firms are instrumental in driving the ban), and share of skilled workers (a highly skilled workforce may also push for the ban in order to reap benefits from higher incentives to innovation). All the characteristics are measured at $t-1$ period. The idea here is to check whether any of these characteristic(s) at a previous period can influence the 1994 ban. The coefficients indicate no statistical correlation between the complementary effect of the Azo-dyes ban and dye-producing firms and any of the firm or industry characteristics. Combining all the above observations, we can conclude that the

[24]We also use, not the interaction term, but only Ban_{94} as the outcome variable of interest; the results remain the same.

[25]We have estimated productivity using Levinsohn and Petrin (2003). This method uses a semi-parametric IV methodology where capital is proxied through use of intermediate inputs. Following Levinsohn and Petrin (2003), we use energy (power, fuel, and water) expenses as the intermediate input. For details, please refer to Levinsohn and Petrin (2003).

ban was exogenous to the prevailing conditions of the Indian labor market.

5 Results: Upstream firms

5.1 First order effects

Before we go to our main results on the effect of the 1994 ban on the demand for managers of the Indian dye-producing firms, we first aim to understand the first order effects of the ban. In particular, we start by discussing how did the ban impacted the product scope of a firm, i.e., the number of different varieties produced, and secondly different production factors viz. innovation expenditure (divided into expenditure on R&D and technology transfer), capital employed, and use of raw materials. We present our results in **Table 3**.

We estimate Eqn. (1) but by substituting the managerial compensation with total number of product varieties produced and different firm level factors of production as the dependent variables. Given the nature of the ban, what we expect is that the ban should first affect the product portfolio of a firm, but negatively. Column (1) regresses the number of product varieties produced by a firm on our coefficient of interest, $Ban_{94} \times Dye_{ij}$. We find that the ban led to about 12.5% drop in product varieties by an average dye-producing firm than other chemical firms. This change in the product portfolio of firms should lead to a change in their factors of production, one of them being managerial input.

Columns (2) – (4) estimates the impact of the ban on the innovation expenditure of the firms. We find: (a) innovation expenditure of a firm significantly increases, and (b) it is significantly driven by the R&D expenditure rather than technology transfer. In fact, the increase in R&D expenditure of a dye-producing firm is six times more than that of the expenditure on technology transfer. This result leads us to the premise that adoption of more R&D or innovation expenditure could impact the higher demand for managers (Damanpour and Schneider, 2009).[26] Lastly, columns (5) and (6) use two other key factors of production: capital employed and the expenditure on raw materials as the dependent variables, respectively. In both cases, we find a positive and significant impact of the ban for

[26] We check for this later in Section 5.3.2.

the dye-producing firms as opposed to firms engaged in the production of other chemicals. Combining all these results, we can conclude that the effect of the ban was contractionary in terms of their product portfolio and expansionary in terms of physical and technological inputs to the production process for the treated group of firms. All these changes in the production processes of the dye-makers could significantly alter the demand for different types of workers within a firm. We explore this in the next section.

5.2 Benchmark results: Azo-dyes ban and managerial compensation

Given the contraction in product portfolio along with engagement in higher R&D related activities as seen from **Table 3**, we explore next what is the effect on managerial compensation. The idea here is that in order to adapt to the ban which makes a key product defunct, the rearrangement in the product portfolio along with increased innovation expenditure would require higher managerial talent and supervision. But, higher managerial inputs on the margin may require not only an increased number of managers, but also a require higher compensation.

We start our analysis by estimating the direct impact of the 1994 Azo-dyes ban on the total and managerial compensation of the focal group of firms, i.e. the upstream firms producing dyes relative to firms in the control group, i.e. the firms that produce other chemicals. **Table 4** presents all the required results by estimating Eqn. (1).

We start by looking at the total compensation in column (1). We do not find any effect of the ban on the total labor compensation of a firm. Columns (2) – (7) use the managerial compensation of a firm as the outcome variable of interest. We find that the 1994 ban led to around 1.3–17.7% increase in the managerial compensation of the dye-producing firms relative to other chemical firms depending on the specification we used.

Column (2) substitutes total labor compensation with managerial compensation as the dependent variable. The ban increased managerial compensation of a dye-producing firm by 4% in comparison to other chemical firms. Column (3) repeats the same but by dropping all the firm level controls (in case they are autocorrelated with the policy shock). The ban continues to significantly affect the compensation of the managers of the dye-producers. Since our post-ban period runs till 2002, it could be possible that the entire effect of the ban driven by some other changes during the end of 1990s, such as delicensing of industries (as a part of the which started around 1998–99. To control for such events, we limit our estimation till 1999 in column (4). Limiting our period of estimation does not affect our benchmark result.

Next, in column (5) we carry out a regression based on Inverse Hyperbolic Sine Transformation (IHS) methodology following Bellemare and Wichman (2020). The reason for doing this is as follows. The earlier estimates handle zeros in the dependent variable in a particular way: by adding 1 to all the values and thereafter taking natural log (thus a value x is transformed into $log(x+1)$), we estimated the model in percentage changes.[27] The coefficient estimate remains consistent and comparable with the earlier findings.[28]

Our results could also be affected by firms exiting the sample. Say, the 1994 ban had the following effect: the firms in the lower tail of the treated group were competed out of the market in 1995. That is, they did not survive the first year following the imposition of the product ban because they are no longer competitive to undertake new innovation for their core product. Then the data for the attriting firms is missing, while the data for the surviving firms remain in the dataset. The latter firms are higher performing, and will have better outcomes on average than the firms that exited (had they not attrited). If such selective attrition/survival is not accounted for in the analysis, this pattern will tend to overstate the effect of the ban, all else equal. Goldberg et al. (2010) argues that the exit rate of firms in case of Indian registered industrial sector is very low, around 5-7%. However, it could still affect our results. In order to explicitly control for the entry and exit issues, we estimate a balanced panel in column (6); our coefficient of interest turns out

[27]Theoretically, a firm cannot spend zero on managerial compensation. Surely, each firm should have at least one manager. But, the dataset only reports an expenditure which is more than 5% of a firm's sales. So, our standard estimates would also include those firms which spends a small amount on managerial compensation.

[28]We have also tested our results using Poisson Pseudo-Maximum Likelihood (PPML), average treatment effect on the treated (ATT) or propensity score estimation, and fractional logit. Our result remains robust to all these estimations (results available on request).

to be significant, positive, but higher in magnitude.[29]

It could be possible that the total amount of managerial compensation has increased, but the share in total compensation remained the same as the total compensation of a firm also increased during the same time period. We now check for this by using the share of managerial compensation in total compensation of a firm in column (7). Using the share also documents a positive effect – the share of managerial compensation in the total compensation of the dye-producing firms increase by around 1.3%.

Although we use the interaction between industry-year fixed effects, our results could still possibly driven by the differences in the pre-trends between our treated (dye-producing firms) and control (other chemical firms) group. To control for such, we interact our treated dummy, Dye_{ij}, with year dummies that can possibly influence our results and plot the coefficients using the following regression equation:

$$\log(y_{ijt}) = (\lambda_t \times Dye_{ij}) + firmcontrols_{it} + \phi_i + \theta_{jt} + \epsilon_{ijt} \tag{3}$$

where λ_t are the year dummies. **Figure 3** plots the year wise coefficients of the differences in managerial compensation between the dye-producing and other chemical firms. Even when controlling for pre-trends, the differences are well-observed. The coefficient plot indicates that the difference between the dye-producing and the rest of the chemical firms in terms of managerial compensation is statistically zero during the pre-ban period, i.e. before the Azo-dyes regulation in 1994. However, an examination of the post-ban period clearly indicates that the managerial compensation rose differentially for dye-producing firms after 1994. In particular, it took a sharp rise in the year following the Azo-dyes regulation and continued to increase further thereafter.[30]

A lot of events happened either due to the ban or going on simultaneously during the

[29] We also explicitly control for exit rate of firms in our sample. We define exit as a dummy, which takes a value 1 when a firm exits our sample after 1994 (except 2002) and is never observed again during the remaining period of analysis. Our benchmark result continues to hold. Similarly, results remain unchanged controlling for entry of firms (results available on request).

[30] We also divide our total managerial compensation into the top and middle managers separately. Both types of managers gain – the coefficients are alike (0.029 and 0.035 with similar standard errors for top and middle managers, respectively). Thus, it could be argued that the within-managers effect is quite homogeneous and pervasive.

1990s. The first is a follow-up domestic ban in 1997. In 1997, the Ministry of Environment and Forests (MoEF) of the Indian government also introduced a similar ban on Azo-dyes following the German ban. It completely banned the production and consumption of Azo-dyes – implying that no leather and textile products treated with Azo-dyes can be sold even in the Indian domestic market. Since 1997 is in the post-treatment period (the German ban was in 1994), clearly this ban may also impact our key coefficient estimate. In particular, it might introduce an upward bias in the direction of the true estimate (since the Indian ban effectively makes the impact of the prior ban even stronger).[31] We address this point by explicitly controlling for the 1997 ban using the following specification:

$$\log(y_{ijt}) = \beta_1 \left(Ban_{94} \times Dye_{ij}\right) + \beta_2 \left(Ban_{97} \times Dye_{ij}\right) + firmcontrols_{it} + \phi_i + \theta_{jt} + \epsilon_{ijt} \quad (4)$$

All other variables retain the same interpretation as in Eqn (1). The only difference is the variable Ban_{97} which takes a value of 1 after the Indian ban in 1997 (i.e. it is 1 from 1998 to 2002). Our estimate from column (8) shows that even though the 1997 ban also significantly affected the managerial compensation of the dye-producing firms, our baseline result continues to hold.[32] In fact, the managerial compensation increased more than 2.5 times after 1997 than between 1995 and 1997.

Next, the Government of India immediately slashed the import duties on the improved high-quality substitutable chemicals from 150—200% to its base rate, 20%. A dye-producing firm may just import the substitutable chemical and sell it to a leather and textile firm. And, the managers might gain from this process. In other words, managers may have the knowledge of the substitutable chemicals that needs to be imported and then sell it to their clients which are the leather and textile firms and this may also increase their compensation. We interact the import of finished products, $MFGds_i$, by a dye-producing firm with Dye_{ij} in column (9) to check whether the increase in managerial compensation

[31] However, the Indian ban is not possibly exogenous. It followed the German ban with a lag of three years, therefore it would be quite natural to assume that the Indian dye-producing firms were already expecting such a ban in the domestic market after the German ban.

[32] In a separate analysis, we restrict our data till 1997. The benchmark result continues to hold (results available on request).

can be explained by this mechanism. We do not find any evidence for such a hypothesis.

Chakraborty and Raveh (2018) show that the drop in input tariffs (as a result of the trade liberalization episode) in India causally affected the demand for managers significantly in the manufacturing firms. Column (10) interacts lagged input tariffs with our treatment variable. The result shows that while input tariffs continue to have significant effects on managerial compensation, our baseline point estimate continues to be significant and positive. In fact, it increases quite significantly while controlling for input tariffs.[33] We additionally interact Ban_{94} with input tariffs in column (11) to control for the idea that the ban itself might drive the Indian government to drop tariffs on certain inputs which are essential to the production of new substitutable dye and this may have driven up the managerial compensation. We find no evidence of such hypothesis.

Lastly, we use total exports of a dye-producing firm in column (12) and its interaction with Dye_{ij}. We use export (a) to control for openness to international markets which might also affect managerial compensation (Caliendo and Rossi-Hansberg, 2012), and (b) as an additional endogeneity check. One might argue that chemical firms were also exporting their chemicals (including Azo-dyes) and that may have triggered the ban rather than transmitting through the leather and textile sectors. If so, the managerial compensation would still be affected as the firms innovate new substitutable products in response to a drop in international sales due to the ban. Our result shows such is not the case – we do not find any effect of the interaction between $Exports_i$ and Dye_{ij}; 'Azo-dyes' ban continues to significantly increase the managerial compensation of dye-producing chemical firms relative to other chemical firms when we control for exports.

Firm level heterogeneity: Which type of firms are driving the results? We start by following Cohen and Klepper (1996) and Endres et al. (2015) to explore the effects on firm size, ownership and the nature of the product (final or intermediate good) in **Table B3 (Appendix B)**. We find that firms of all sizes except the small firms[34], both domestic and

[33] If we replace input tariffs with import of raw materials done by firms – we find similar effects.

[34] We divide firms into four different size quartiles based on the assets of the corresponding industry to which they belong. Putting it differently, if a firm's asset is below 25th percentile of the total assets of the industry to which it belongs, it would be classified as 1st quartile firms and the dummy Qr_i where $i = 1, 2, 3,$ and 4 would take the value 1 and so on.

foreign firms (with the effects larger, but albeit weak for foreign firms), and firms producing intermediate goods[35] drive the main result.

5.2.1 Extensive margin and Non-managers

Our results above show that the 1994 ban significantly affected the intensive margin of the demand for managers. Two issues remain to be addressed: (a) it could be possible that the compensation or value of existing managers increased without any change in the extensive margin or the demand for new managers; (b) what happened to the non-managers? Is this increase in the managerial demand accompanied by a similar increase or an opposite effect? In other words, is the demand for managers increased at the expense of non-managers? To explore these questions, we now evaluate the effect of the Azo-dyes ban on the number of managers, average wage of the managers, number of non-managers, and non-managerial compensation. Results are reported in **Table 5**.

Before, we get on to the estimations of the extensive margin following two points are worthy to be noted: (a) PROWESS does not report the number of employees data across the full spectrum of employee categories very consistently across firms and over time. In case of number of managerial employees it only reports top and middle managers names (also not very consistently) and not numbers. We count the names of the managers in order to find out the number of managers; and (b) our dataset when using the extensive margin of managers and non-managers as the dependent variable drops to about 1/10th of the total observations. So, there may be possible questions regarding the external validity of the results. We do not claim that our results from using such limited data can be generalized, but it still gives an approximate idea of what happened at the extensive margin of the labor composition of firms.

We start by using the number and average wage of managers in columns (1) and (2). We find positive and significant effect on both counts. The ban also had about 17% effect on the hiring of new managers, whereas the average wage also increased by about 8.3%.

[35] This is certainly what we expected. Azo-dyes is an intermediate input (by end use) which is used by the leather and textile firms for the production of their final products. Therefore, it is imperative that the increase in demand for managers would be driven by firms whose end product is an intermediate good.

Columns (3) and (4) look at the non-managerial component – the former uses the number and the latter compensation, respectively. We find that the 1994 ban negatively affected the both the extensive and intensive margin of the non-managerial workers. This result also highlights one additional mechanism through which there may have been an increase in managerial demand – substitution between managerial and non-managerial workers. In other words, although our results indicate no trade-offs between intensive and extensive margin of managers, but they indicate a trade off between managers and non-managers.

Combining all these results we can infer that an international product ban, due to environmental concerns, significantly increased the demand for managerial input while simultaneously reducing the demand for other kinds of workers. There could be many reasons why such an effect could occur, i.e., development of a new product, adoption of more technology, importing new intermediates, etc. In the next sections, we explore all the possible mechanisms.

5.3 Tracing out the mechanism

5.3.1 Changes in the product portfolio

We now explore the mechanisms that could potentially explain why the regulatory ban can lead to an increase in the managerial compensation. We start by looking at the product portfolio of firms.

Our chain of arguments is as follows. With the ban coming from one of the main export markets of the leather and textile firms, the demand for that product (Azo-dyes) by the leather and textile firms from the chemical firms would immediately drop to zero. This would affect the product portfolio of those firms negatively; this is what we find in **Table 3**. The resulting effect is straightforward: in anticipation that the leather and textile firms can start importing the substitute chemical,[36] a representative dye-producing firm would want to immediately change its product portfolio as a significant portion of their customer base would be lost otherwise.

[36] India was going through a trade liberalization episode during the same timeframe around 1994 and as a part of the reforms, input tariffs were dropped significantly over the years.

In addition, if the ban affected the core product or one of the main products of a dye-producing firm, it would immediately start innovating for the new substitute product considering the long-term prospect of the firms to sustain themselves in the same product market (exiting a market where they have already built their production capabilities along with sales and distribution channels, and entering a new market with new products is enormously costly). Developing a core product would require reallocation of their resources along the product lines, such as the managerial inputs. The firms can do so by focusing more on the core product and shedding their peripheral products.[37] It would not be entirely unplausible to expect that firms would focus more on their primary products in order retain and enhance their comparative advantage and efficiency.

We test for this mechanism using the following specification:

$$\begin{aligned} y_{ipjt} &= \beta_1 \left(Ban_{94} \times Dye_{ij}\right) + \beta_2 \left(Ban_{94} \times Dye_{ij} \times Core_{ip}\right) \\ &+ firmcontrols_{it} + \phi_i + \lambda_p + \theta_{jt} + \epsilon_{ipjt} \end{aligned} \tag{5}$$

y_{ipjt} takes a variety of dependent variables – product exit, product entry, core product, product scope, sales share of the core product, product quality, quantity sold and varies at the firm(i)-product(p) level. $Core_{ip}$ is a dummy for the core product (p) of a firm (i) and λ_p represents the product fixed effects. All other variables remain the same. To test for Eqn. (5), we employ firm-product level data from PROWESS. One of the unique features of PROWESS is that it gives detailed data at the product level of a firm including the name of the products (a firm produces), its sales, quantity sold, etc.[38] We report the results in **Table 6**.

We start by looking at product exit (column 1) and product entry (column 2) of a firm. We define product exit as the variable that takes a value 1 if we do not observe a product in the following year in the sample. In the case of product entry, the variable takes a value of 1 if and when a new product appears in the sample. We report marginal

[37] Studies in trade such as Baldwin and Gu (2009), Carsten and Neary (2010), Liu (2010), Mayer et al. (2014), and Chakraborty and Henry (2019) show that in response to higher import competition firms shed their peripheral or least popular products and focus more on the core ones.

[38] This particular aspect of the data set has been previously utilized by De Loecker et al. (2016).

effects. Our estimates show that there is a 5% chance (at the mean) of a firm to drop its product in response to the ban, whereas there is about a 1% change of a new product being introduced in the market. This implies evidence of a significant product churning for the dye-producing firms with net product exit from the market. Next, we look at how does this product churning got reflected in the core and peripheral products of a firm.

In the 1990s, Azo-dyes was one of the most popular chemicals used by a leather and textile firm and it was around 70% of all the dyes being used. Given this, it would not be hard to imagine that Azo-dyes could be the core product for a large sample of firms. If that is the case, then with the ban, developing a new substitute core product would be of the first order importance. And, the value of managerial input would increase significantly. We test for this proposition by using a core product dummy as the dependent variable in column (3). We identify the core product of a firm as follows: it takes a value of 1 if a product is the core product of a firm. We label a product as the core product of a firm if the average sales of the product (over the years 1989–2002) is greater than 70% of the total sales of a firm (across its all products).[39] We find that there is a 8% chance that the ban could impact the core product of a firm. If such was the scenario, a representative dye-producing firm would drop its least popular products and concentrate on the core products. Column (4) interacts $Core_{ip}$ with our main variable of interest and use the total number of product varieties produced by a firm as the dependent variable. We find that the triple interaction term is negative and significant. This implies that in response to the ban dye-producing firms started to drop its peripheral products. This result consolidates the idea of product concentration even further.

To explicitly check for this hypothesis on product concentration, we calculate the sales share of the core product of a firm. PROWESS gives detailed sales data by each product of a firm. We calculate the share of sales of each product as a ratio of total sales of a firm, its change (first-order difference) and regress on $Ban_{94} \times Dye_{ij}$ and $Ban_{94} \times Dye_{ij} \times Core_{ip}$ in columns (5) and (6). The latter turns out to be positive and significant in both cases implying that sales share from the core product of a firm increased significantly. In par-

[39] We follow Goldberg et al. (2010) for the definition of core product. We also experimented our results with 60 and 80%, but the result does not change.

ticular, the change in the sales share of a firm from its core product increased by around 12%, whereas it dropped by 4.3% in the case of their peripheral products.

Lastly, we check for the quantity of output sold and quality upgrading in columns (7) and (8), respectively. Our point estimates show that the ban resulted in an increase in quantity sold and quality (we use the unit price of a product as an indicator of quality) of a product for dye-producers. Overall, these results indicate that the Azo-dyes ban in the process led to a significant product concentration and quality-upgrading for the dye-producing firms.

Our results on product churning are completely consistent with those found in (Levinson (2009); Shapiro and Walker (2018)). They argue that changes in environmental pollution from manufacturing can be attributed to three different factors: (a) scale, (b) composition, and (c) technique. The former relates to the scale of manufacturing output, while the latter two explains the changes in the composition of the products produced, and environmental damage per unit of product produced. Like Shapiro and Walker (2018), our results also portray that environmental regulation forces in our case the input sector to make significant changes in product composition resulting in a decline in environmental damage, post the regulation.

5.3.2 Factors of production

After establishing that change in the product concentration could play a major role in the increase in the demand for managerial input, we now directly test whether product churning and changes in other factors of production could lead to an increase in managerial compensation or not.

To test for such hypotheses, we use the following triple-diff specification:

$$\begin{aligned}\log(y_{ijt}) &= \beta_1\ (Ban_{94} \times Dye_{ij})\ +\ \beta_2\ (Ban_{94} \times Dye_{ij} \times R_i) \\ &+ \ firmcontrols_{it} + \phi_i + \theta_{jt} + \epsilon_{ijt} \qquad (6)\end{aligned}$$

R_i is a vector which represents the core product of a firm, production and innovation-related variables of firm i. We consider R&D expenditure, technology transfer as innovation- and import of intermediate inputs (raw materials and capital goods), and total employed capital as production-related factors. All these are represented as dummy variables. Our coefficient of interest is here both β_1 and β_2. While the former captures the baseline effect, the latter signifies what happened to a firm in case it undertakes say, R&D expenditure, technology transfer, imported intermediate inputs, employed more capital, etc. In other words, it captures the net responses on the managerial compensation for firms in the treatment group in the post-1994 period with higher innovation and other production-related activities, over and above the firms in the control group (i.e., the firms producing other chemicals). The results are reported in **Table 7**.

We start by regressing total managerial compensation on the interaction between the core product of a firm, $Core_{ip}$ and $Ban_{94} \times Dye_{ij}$ in column (1).[40] Our estimates show that the triple interaction term is positive with the double interaction being the opposite. This implies that the effect on the managerial compensation due to the ban is driven by the core product and not the overall product churning of a firm. This further establishes our conjecture that changes in the product portfolio of a firm, especially designing a new core product, require significant managerial inputs and would increase the demand for managers both within and between dye-producers and other chemical firms.

Column (2) substitutes the core product of a firm by the R&D expenditure. Based on the results from the previous section, we can possibly argue that because of the ban the main product for the dye-producers could receive a threat of extinction. If a substantial portion of the firms were dependent on Azo-dyes as their core product, it is likely that they need to adapt to the new scenario by altering their product portfolio by producing similar products.[41] In such a scenario, it is certainly plausible that the expenditure on research and development can increase significantly. Following this, the dye-producers may require more skilled managers to manage the new stream of innovation and R&D activities. Our

[40]In this case, we are running the regressions at firm-product level. Please note that the number of observations increase three times.

[41]Producing a completely new product line would be extremely costly due to fixed cost for production as well as the cost of employing new labor with different skills and/or endowing new skills on the pre-existing pool of labor.

estimate suggests something similar. Firms which undertake R&D expenditure experience a large increase in managerial compensation compared to firms who do not. The difference between these two types of firms is around 8 times. We see some indirect evidence for *compensate to innovate*. Our results are similar to what Acemoglu et al. (2006) find with a theoretical model. The model points out that the demand for managers will increase with higher innovation as a country moves closer to the technological frontier, and the opposite happens when the same does more imitation.

Columns (3) use technology transfer as one of the explanatory variables. It could be possible that instead of innovating the product, the dye-producing firms in India seek help from the foreign firms in terms of buying, adapting the new substitute chemical and in the process, the value of managers increased (as they are in a position to facilitate the process). We find such is not the case.

Imported inputs make an important source of technology inflows, especially in the developing economies. These, in turn, may lead to changes in firms' production technologies, demand for managing the new incoming knowledge, requiring labor adjustments in favour of managers in terms of training, and problem solving. We use import of intermediate inputs (raw materials plus capital goods) as one of the explanatory variables in column (4). We find that import of intermediates as a result of the ban by the dye-producing firms resulted in an additional 5.5% increase in the compensation of the managers. Lastly, we use total capital employed of a firm in column (5). The ban might induce firms to adopt more capital-intensive technology and this may increase the compensation of the managers. We find no evidence of such a hypothesis.

5.3.3 How to compensate for innovation?

The above discussion brings us to the question of how do the firms compensate their managers to innovate? The recent literature suggests two view-points. The idea that innovation requires compensation is not surprising. What is surprising is that some kind of compensation can actually be counter-productive. For example, Ederer and Manso (2013) show that pay-for-performance could be detrimental to innovation. The crucial insight is that the type of activities that require higher levels of efforts and productivity, can be incentivized by pay-for-performance metrics, whereas rewarding long-term success may be more effective in fostering innovation. We now decompose the total compensation for managers and non-managers into the wage and incentives component in **Table 8**. In our data, we capture the pay-for-performance measure via bonus or incentives that the workers obtained.[42]

We estimate Eqn. (1) by substituting managerial and non-managerial compensation with wages (which is the fixed component of the total compensation) in columns (1) and (2) and incentives (the variable component of the total compensation) in columns (3) and (4). Our results show that managers of the dye-producing firms earn a higher wage in the post-treatment period while receiving no additional incentives (that reflects pay-for-performance measures), whereas the non-managers only lose the incentives leading to a net fall in their total compensation. Given the long-term nature of the change, in the product market due to the ban, it is highly natural for firms to incentivize the managers by rewarding more for long-term rather than short-term success. This type of change in the compensation structure for managers is quite consistent with the literature on incentivizing innovation for the long-term (Ederer and Manso, 2013).

5.4 Firm performance

We close this section by looking at what happened to those dye-producing firms after the regulation in terms of their overall performance in **Table 9**. We use total sales, exports, profits after tax, and total productivity of a firm as the outcomes of interest.

Theoretically, we should not find any effects on either sales or exports or profits. The

[42] Our discussion also addresses one important question that might arise as to whether the dye-producing firms truly considered the German ban to have a permanent impact on the Indian market or not, i.e., when the ban happened. This is crucial because if they were not expecting the effect to be permanent, then potentially the need for innovation also would have dissipated and therefore, the corresponding impact on the labor compensation would also have dissolved. In an ideal world, we would like to survey the managers to know their exact decision-making points. However, given that the event happened 27 years back from now, it is not possible to recover such ground-level managerial information. Secondly, we know that the Indian government followed the German ban and introduced a similar ban in 1997. Given that these kinds of bans will have after-shocks, it is natural to expect that the dye-producing firms started to respond immediately rather than waiting for another ban (domestic in this case) to materialize. In other words, if we control for the 1997 Ban, the results remain the same – wages respond and not incentives.

initial effect of the ban should be negative on sales and profits of a firm. On the other hand, as the firms start to reorganize their production technology in terms of innovating and/or producing the new substitute chemical, their sales and profits should start to increase. In terms of the overall effect, there are three possibilities: (a) these two effects should cancel each other; (b) the negative outweighs the positive effect; and (c) vice-versa. In terms of productivity, we expect to see a positive effect as the firms now concentrate more on their core product and use their resources efficiently.

Columns (1), (2), and (3) use total sales, exports, and profits of a firm as the outcome variables, respectively. We find some evidence of negative effects on profits of a firm. Lastly, we use total factor productivity of a firm in column (4). As expected, we find that the ban led to about 9% increase in the total factor productivity of a dye-producing firm. This can be seen in the context of what Shapiro and Walker (2018) finds theoretically that pollution intensity or environmental damage of a firm decreases with productivity. Overall, our key finding is that while the stringent standards may have added to the costs (in terms of finding for new, safe, high-quality chemical) of the dye-producing firms, the presumed trade-off between compliance and competitiveness (in terms of productivity) did not materialize.

Summarizing our results from the effects of the NTB, or the Azo-dyes ban, on the upstream sector, we note that (a) it is the combination of changes such as product churning, undertaking of higher R&D, import of intermediates due to the ban that led to increase in demand for managerial workers in dye-producing compared to other chemical firms; (b) it is the fixed component of wage which drives the increase; and (c) firms experience a drop in their profits, but increase in productivity. We now turn our focus to the downstream sector (leather and textile firms) to which the ban was primarily targeted.

6 What happened to the downstream sector?

We now analyze the impact of the 1994 Azo-dyes ban on the downstream firms. Based on our previous results, we argue that managerial compensation of the dye-producing firms increased relative to other chemical firms, as a result of the ban since managerial input was essential to (a) alter the product portfolio, especially for the core product; (b) innovation, especially R&D expenditure for the development of a new substitute product; and (c) import of intermediate inputs. Our goal here is to check whether there are any effects of the ban on these outcome variables of interest for downstream firms. If not, then there should not be any positive effect on the managerial compensation for these firms. Overall, these results would further help us to establish our mechanisms even stronger.

Two additional reasons also drive this exercise. First, our results would also portray whether there are any spillover effects from the upstream dye-producing firms. This is in relation to what Liu (2019) proposed. He argued that targeted policy interventions at one part of the supply chain connecting the industries in an economy could lead to distortionary effects due to backward demand linkages. In our case, it is not the backward, but forward demand linkages. For example, managerial input may be required in the leather and textile firms to adapt to the new substitute chemicals that the dye-producing firms produced. Or, it could be the opposite. Straightforward use of the new chemical or consultation by the dye-producing firms (to adopt the new chemical) may also lead to no effect or drop in managerial demand for leather and textile firms.[43]

Secondly, there is a large literature on the diffusion of regulatory impacts on the supply chain for both the focal and non-focal firms (see e.g. Lanjouw and Mody (1996); Levi-Faur (2005); Greaker and Rosendahl (2008); Calel and Dechezleprêtre (2016)). Overall, it is imperative to check for the effects of the Azo-dyes ban on the downstream firms. We use the following equation:

$$y_{ijt} = \beta\,(Ban_{94} \times LT_{ij}) \ + \ firmcontrols_{it} + \phi_i + \theta_{jt} + \epsilon_{ijt} \tag{7}$$

y_{ijt} is a vector of dependent variables – domestic raw material expenditure, imported raw materials, total products produced, core product, R&D expenditure, and managerial com-

[43]Liu (2019) shows that size distortions are more for upstream and relatively less for downstream sectors. This is a very useful result as it provides a benchmark to compare our results. We show that our empirical results are consistent with this although, strictly speaking, the industrial policy of favoring certain sectors in his work is opposite to the ban that we consider here as a treatment (albeit both are external interventions and are institutionally similar).

pensation. In the case of the total number of products produced and core product, y_{ijt} becomes y_{ipjt}, where p denotes a product of a firm. This is because we then employ firm-product-year level data instead of firm-year.

LT_{ij} takes a value 1 if a firm i belongs to the leather and textile sector (j). Our classification of leather and textile firm is at the 2-digit industry level. Since, our key variable of interest, $Ban_{94}\times LT_{ij}$, now varies at 2-digit industry-year level, θ_{jt} denotes interactions between industry fixed effects at 2-digit level and year trends. We now cluster standard errors at the 2-digit instead of 5-digit level as we were doing it previously.

Now, our treated group comprises the leather and textile firms and the control group the 'other manufacturing' sectors (less chemical). The reason for our choice is straight-forward. Firms producing leather and textile goods are the ones who use dyes in their production process as one of the primary inputs. Thus a ban on dyes would immediately impact their production process unless the dye-producing firms innovate in such a way that the effect is contained within the dye-producing firm and not transmitted downstream. Since a control group should be unaffected by the shock but should exhibit a behavioral pattern closely similar to the treated group in the pre-treatment period, we use other manufacturing sectors (all manufacturing minus chemical) as the appropriate control group.[44]

We estimate Eqn. (7) and report the coefficient estimates in **Table 10**. We divide the table into two parts: columns (1) – (5) checks for the possible mechanisms or the reasons behind the increase in managerial compensation, while columns (6) – (9) estimates the effect of the ban directly on managerial compensation.

We start by looking at two different types of raw material expenditure – domestic

[44]One can still argue that the most ideal control group would be a sub-sector within the leather and textile industries that does not use dyes as an input (for example, footwear). We argue that even this choice still does not completely resolve the problem. There could be high mobility of workers across different sub-sectors of leather and textile, implying that choices of such sub-groups (within leather and textile) as the control group would not still qualify for exogeneity. There is another factor influencing the choice here. There were macro reforms in the form of tariff reductions, FDI liberalization, etc in the same time frame. If one looks for some sectors that were very unlikely to be affected by the Azo-dyes ban (for example, service sector) and treat it as the control group, it has an obvious problem of being affected by trade reforms. Additionally, there is absolutely no reason to believe that other unrelated sectors (like service) would show similar patterns as the leather and textile sectors in its production and compensation. Thus avoiding both types of shocks (Azo-dyes ban as well as FDI reform) along with satisfying the criteria of exhibiting similar trends at the industry level during the pre-ban period, is almost impossible. Therefore, we consider our choice to be an appropriate compromise.

and imported in columns (1) and (2), respectively. As a result of the ban, a leather and textile firm may start substituting one of their key raw materials, Azo-dyes with the newly available substitute either developed by the dye-producing firms or simply importing it (if the substitutes are readily available). And, this may result in an increase in their raw material expenditure. The coefficients show that the ban led to about 5% increase in the domestic raw material expenditure and a simultaneous decline in 1.8% of the import of raw materials for the leather and textile firms confirming that the substitutes of the Azo-dyes were not readily available in the international market and was developed by the dye-producing firms in India.

Next, we check how the product portfolio of the leather and textile firms got affected as a result of the ban in columns (3) – (4). Overall, our results do not indicate any effect of the 1994 Azo-dyes ban either on the total product scope or core product of a leather and textile firm. Lastly, in column (5) we examine the effect on R&D expenditure; we find that the Azo-dyes ban led to around 4.7% drop in the R&D expenses for the leather and textile firms.[45] Overall, we do not find any consistent effect on the 1994 ban on the key outcomes (which affects managerial compensation) of the leather and textile firms.

Columns (6) – (9) check for any changes in managerial compensation. Given what we find in columns (1) – (5), we expect to find no effect on the managerial compensation. This is because: increase in the demand for managers is highly correlated with new or non-routine tasks within a firm. And, undertaking of R&D investments or importing of new intermediates to produce a new substitutable core product or changes in the product scope falls into such category. And, we do not find evidences of any such changes for the leather and textile firms. The results clearly show a limited response of the ban on managerial compensation for downstream firms. Our coefficient of interest is indistinguishable from zero across all the columns.

Following Tewari and Pillai (2005), we note that this could be due to the following reason: the costs of compliance for the leather and textile firms went up significantly as the

[45]This is similar to what Chakraborty and Chatterjee (2017) find. They argue that since the innovation happened at the upstream sector, it had a dampening effect on the same in case of the downstream sector firms. Theoretical studies in the industrial organization literature also highlights that competition can have downward effect on innovation (Aghion et al., 2005).

ban, though inadvertently, turned the input industry (the dye-producers) of the leather and textile firms into de facto diffusers of environmental compliance. Forced to shift to safer dyes, the dye-makers, began experimenting with the development of substitutes, launched efforts to market them and then provided technical consultations to their primary clients, which are the leather and textile firms, to adapt it without any major changes to their production processes. All these efforts by the dye-makers helped the leather and textile firms to adapt to the new input with no significant changes in within-firm labor composition. Efforts to develop the new product and further helping their clients to adapt it induced changes in within-firm labor force composition for the dye-producers and not the leather and textile firms (for which only expenditure on raw materials increased).[46]

To put our results into the context of spillover of regulatory effects through supply chains, one can a priori guess that the burden of the regulatory shock would be shared by both the input (or upstream) and the focal downstream sector. Whether the shock is contained within the focal sector or not, will depend on the relative importance of the shock to that sector. In our case, the results show that the effects of the ban are majorly absorbed by the upstream firms themselves as the innovation, in terms of the new substitutable product, happened in the upstream sector. And, these changes significantly explained the increase in the value of the managers in a dye-producing firm.

7 Discussion and Conclusion

How do NTBs impact labor markets? We evaluate this question by exploiting the exogenous event of a ban of any leather and textile products (both exported and domestically produced) treated with Azo-dyes by Germany in 1994 due to health and environmental hazard on within-firm labor choices.

The ban on the products of leather and textile industries (which are downstream)

[46] In the process, the earnings from exports for the leather and textile firms increased. **Figure C1 (Appendix C)** plots the total exports of leather and textile goods to the World and the EU for 1990–2002 using the UN-COMTRADE database. Export flows continue to increase even in the post-regulation period. Tewari and Pillai (2005) argues that the Ministry of Commerce, Govt. of India also helped the leather and textile firms to adapt the newly substitutable chemical because its core mission of promoting trade was at stake.

became a *de-facto* product ban for the upstream industry, dye-producers. This event changed the dynamics of the dye-producing firms in India in terms of changing their product portfolio (innovating a new substitute product, dropping the peripheral products, and concentrating more on the new core product), spending more on R&D, importing more high-quality intermediates and in the process increasing the value of the managers relative to other types of chemical firms. Broadly speaking, we show how a non-tariff barrier through regulatory spillovers create labor market repercussions, leading to a divergence of compensation between the managers and non-managers by 1.3–17.7%. Our finding is persistent, economically meaningful, robust to a myriad of tests, and potential channels.

With this study, we address two fundamental questions. First, how does our findings enhance our understanding of the economic impacts of NTBs or cross-border environmental regulations? Second, what are the potential underlying mechanisms that drive our results? In an attempt to answer these questions, we build a conceptual framework borrowing elements from empirical and theoretical literature that brings the above findings together.

Starting with the former, the main finding of this study sheds new light on the central issues related to firm level impacts of NTBs; especially those related to managerial inputs, firm performance, and growth. This result fits into a growing body of empirical literature that links management practices to firm level economic performances captured by productivity, quality and growth (see for example Garicano (2000); Garicano and Rossi-Hansberg (2004, 2006); Bloom and Reenen (2007); Bloom et al. (2013); Caliendo et al. (2015), etc.). There is a long list of literature which documents such effects due to trade (see e.g. Cunat and Guadalupe (2009); Ma and Ruzic (2020); Olney and Keller (2021)), but studies related to NTBs are limited.[47]

Our paper is a first attempt to fill this gap and provide an empirical direction to the literature.[48] To summarize, our results focus on a relatively understudied link between a

[47]Previous research indicates that trade liberalization or globalization or product market or import competition has profound effects on labor markets through intensifying the competition in terms of a price shock, new inputs, technologies, products, etc. The literature overlooked the impacts of other kinds of trade barriers, which are non-tariff in nature, on labor markets. Broadly speaking, our analysis is situated within the sparsely populated literature studying dynamics of firms in developing economies within the context of globalization, organizational structure and task specification (Atalay et al., 2020; Duval-Diop and Grimes, 2005). We thank Alan L. Winters for suggesting this point.

[48]Although Navaretti et al. (2020) is the first study to show that NTBs (in their case, TBTs) also have

NTB (in particular a SPS measure as it originated due to health hazards), product portfolio, innovation, and labor compensation.[49]

Secondly, there is a overwhelming amount of empirical literature that highlights significant effects of NTBs on various firm level attributes. We identify four key outcomes: (a) innovation (Jaffe and Palmer, 1997); (b) technical change (Calel and Dechezleprêtre, 2016); (c) product choice (Lipscomb, 2008) and (d) productivity (Perkins and Neumayer, 2012). All these four outcomes suggest that dye-producers undergo a demand shock. Firms that experience such a shock increase the importance of managerial inputs, based on the notion of knowledge hierarchies (Garicano, 2000), whereby firms economize on the problem solving process. This is consistent with the observed increase in R&D expenditure, changes in product portfolio, import of intermediates, etc. pointing towards a quality upgrading mechanism. All these technical changes suggest that the demand for development of a new formidable substitute (which includes new knowledge arriving via R&D expenditure, etc.) yields an organizational change that in turn increases the demand for managers, manifested via increases in their wages and number.

We also emphasize the role of capital-skill complementarity.[50] Our findings indicate that the regulation increased capital employed and R&D expenditure of dye-producing firms, which in turn positively affected the share of managerial compensation and drop in non-managerial. Since managers are typically considered to be skilled labor,[51] our results are also consistent with capital-skill complementarity to be a potential channel.[52]

Lastly, our paper also fits and provides result consistent with the larger context of policy transmission through input-output production network (Liu, 2019). This literature is new

similar effects (increase in the share of managers), but the findings are limited in terms of the scope of the effect.

[49]We note two limitations of the present analysis. In an ideal world, we would want to use (a) an employer-employee data set to measure the effects across various occupational groups; and (b) information on patents. Our data set allows us only to focus on aggregate variables including employment, compensation and product churning indicating entry and exit.

[50]The idea that capital-skill complementarity leads to capital substituting low-skilled labor is well recognized in the literature (see e.g. Griliches (1969); Krusell et al. (2000)).

[51]While it is plausible to assume that managers are skilled, it is not the case that all the skilled are managers; some will inevitably be non-managers.

[52]However, we find that our effect is not entirely driven by this channel. We use industry level skill intensity (ratio of non-production workers to total employees) as a control variable and show that our benchmark results are robust to the inclusion of this control (result available on request).

and there is still a clear dearth of empirical demonstration of such shocks propagating from downstream to upstream firms. However, our present dataset does not allow us to observe the firm-to-firm linkages and hence, we cannot fully pin down such transmission pathways.

We note that from a policy-perspective the emergence of innovation-driven inequality in the context of a developing country necessitates policy intervention from the point of view of a social planner, in the presence of institutional void (Palepu and Khanna, 1998) and lack of safety mechanisms for less skilled workers. This problem accentuates in presence of frictions when firms cannot exit the market as is often the case in developing economies where exit costs can be relatively high. Thus in countries with stronger institutions, the same shock may lead to inefficient firms exiting rather than trying to innovate. This raises a possibility of trade-off for a firm choosing to pay the cost for exit or innovation. In the present context, the Azo-dyes regulation came in the form of a policy which targeted the leather and textile firms with significant spillover implications for dye-producing firms. While this is very useful for sharp and accurate identification, we note that environmental regulations are often of a bigger scale and cover larger ground (see e.g. the work by King et al. (2019) on the effects of carbon taxes in presence of externalities) leading to general equilibrium effects. Our approach allows us to conduct the analysis in a partial equilibrium framework. Characterizing the effects with general equilibrium responses in the supply chain is a new and upcoming field of analysis (Liu, 2019) as noted above. Our empirical results provide one step in that direction.

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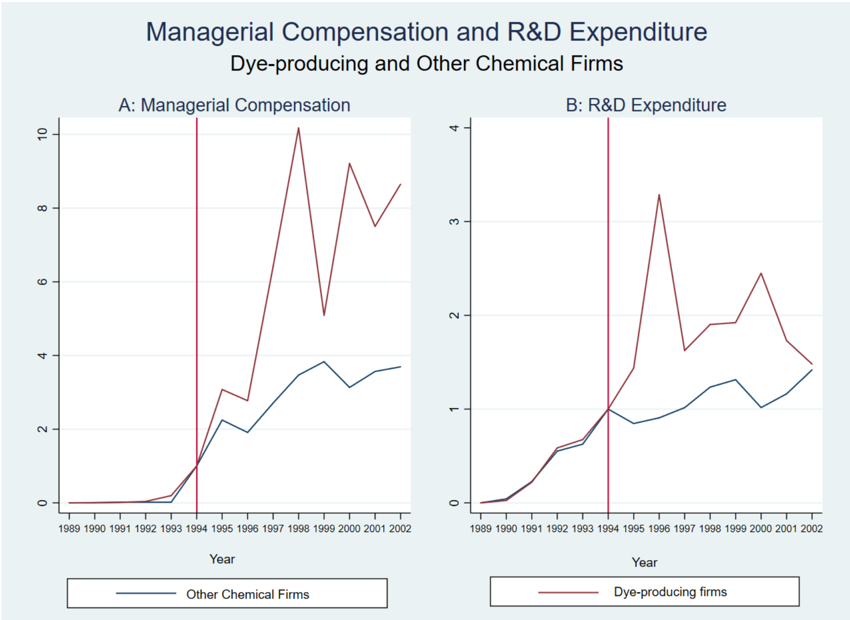
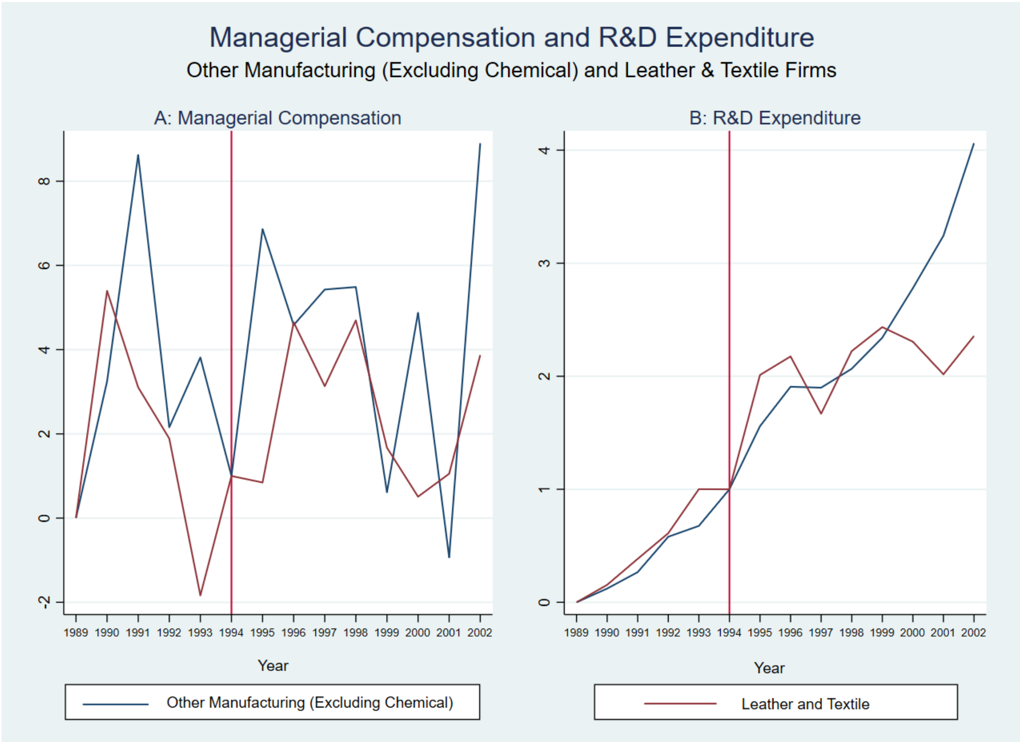
Figure 1: Managerial Compensation and R&D Expenditure: Dye-producing and Other Chemical Firms



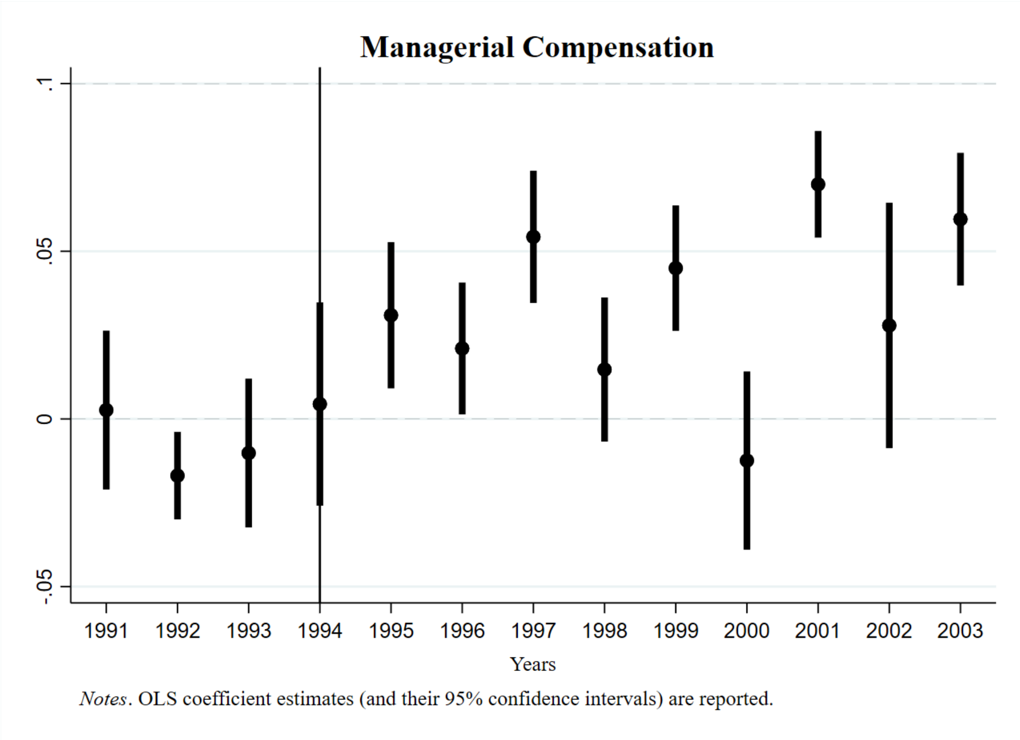
Note: This figure presents the normalized value of managerial compensation and R&D expenditure for dye-producing and other chemical firms for 1989-2002. We calculate a simple correlation between managerial compensation and R&D expenditure of firms for dye-producing and other chemical firms. In case of the former, the correlation coefficient is 0.76, whereas in case of the latter, the same is 0.05. Although, both significant at 5% level.

Figure 2: Managerial Compensation and R&D Expenditure: Other Manufacturing (Excluding Chemical) and Leather, Textile Firms



Note: This figure presents the normalized value of managerial compensation and R&D expenditure for leather, textile and other manufacturing (less chemical) firms for 1989–2002.

Figure 3: Azo-dyes Ban and Differences in Managerial Compensation: Coefficients Plot



Note: This figure presents yearly coefficients in terms of the differences in the managerial compensation for dye-producing and other chemical firms for 1991–2003.

Table 1: Correlation: R&D Expenditure and Managerial Compensation

	R&D Expenses	Technology Transfer	R&D Expenses	
			Yr $\leq$ 1994	Yr $\geq$ 1995
	(1)	(2)	(3)	(4)
	Managerial Compensation			
Dye-producing	0.63*	–0.009	0.42*	0.71*
Other Chemical	0.05*	0.006	0.13*	0.05*
Leather and Textile	0.18*	0.04*	0.16*	0.18*
Other Manufacturing	0.19*	0.03*	0.08*	0.22*

Notes: Numbers shows simple pairwise correlations. A dye-producing firm to the category "20114" (5-digit NIC 2008) that is – *Manufacture of dyes and pigments from any source in basic form or as concentrate*. Other Chemical firms belong to other 5-digit codes of the 2-digit code 20 (NIC 2008), which is the "Chemical Industry". A leather and textile firm belongs to 13, 14, and 15 of 2-digit NIC 2008. Other manufacturing is less of textile, leather, and chemical firms. * denotes statistical significance at 5%.

Table 2: Endogeneity Checks: 'Azo-dyes' Ban

	Managerial Compensation		$Ban_{94} \times Dye_{ij}$			
	(1)	(2)	(3)	(4)	(5)	(6)
$Dye_{ij} \times Year_{91}$	–0.004					
	(0.003)					
$Dye_{ij} \times Year_{92}$	–0.038*					
	(0.024)					
$Dye_{ij} \times Year_{93}$	–0.008					
	(0.006)					
Ban_{t-3}		0.072				
		(0.055)				
Ban_{t-2}		0.024				
		(0.023)				
Ban_{t-1}		–0.029				
		(0.018)				
Managerial $Comp_{it-1}$			0.00003			
			(0.00003)			
Capital $Employed_{it-1}$				–0.003		
				(0.003)		
TFP_{it-1}					–0.001	
					(0.003)	
Skill $Intensity_{jt-1}$						–0.466
						(0.634)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
R-Square	0.23	0.43	0.15	0.15	0.15	0.07
N	11,207	11,207	10,638	10,612	10,571	9,405
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	No	Yes
Industry FE (3-digit)*Time Trend	No	No	No	No	No	Yes
Industry FE (4-digit)*Year FE	Yes	Yes	Yes	Yes	Yes	No

Notes: Columns (1) – (2) use 'total managerial compensation' of a firm as the dependent variable. Columns (3) – (6) use the interaction between Ban_{94} and Dye_{ij} as the dependent variable. Ban_{94} is a binary variable indicating the ban, which takes a value 1 when the year is greater than 1994. Dye_{ij} is a firm level dummy variable, which takes a value 1 if a firm belongs to the category "20114" (5-digit NIC 2008) that is – *Manufacture of dyes and pigments from any source in basic form or as concentrate*. We use the chemical industry minus the dye-producing firms as the control group. $Year_{91}$, $Year_{92}$, and $Year_{93}$ are binary variables indicating the years in the subscript. These take the value 1 for the respective years. Ban_{t-i}, where $i = 1$, 2, and 3 takes a value 1 for the years less than 1994 by 1, 2, and 3 years, respectively. *Managerial* $Comp_i$, *Capital* $Employed_i$, and TFP_i are managerial compensation, capital employed, and total factor productivity. All these are at the firm level. TFP is the total productivity of a firm based on Levinshon-Petrin methodology (Levinsohn and Petrin, 2003). *Skill* $Intensity_j$ is defined as the share of non-production employees to total employees at the 3-digt NIC 2004. 'Firm Controls' include age, age squared, size (assets) and technology adoption expenditure. Numbers in the parentheses are robust standard errors clustered at the 5-digit industry level. ***, **, * denotes statistical significance at 1%, 5%, and 10%.

Table 3: 'Azo-dyes' Ban and First Order Effects: Upstream (Chemical) Firms

		Factors of Production				
	Product Scope	Innovation Expenditure	R&D Expenditure	Technology Transfer	Capital Employed	Raw Material Expenditure
	(1)	(2)	(3)	(4)	(5)	(6)
$Ban_{94} \times Dye_{ij}$	–0.125***	0.069***	0.072***	0.012***	0.117***	0.039*
	(0.038)	(0.024)	(0.026)	(0.002)	(0.044)	(0.022)
R-Square	0.91	0.72	0.71	0.20	0.85	0.83
N	33,949	11,193	11,193	11,193	11,193	11,193
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Product FE	Yes	No	No	No	No	No
Industry (4-digit)*Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Columns (1) – (6) use product scope (number of product varieties produced), total innovation expenditure (expenditure on R&D and Technology Transfer), only R&D Expenditure, only Technology Transfer expenditure, Capital Employed, and Raw Material Expenditure of a firm, respectively as the dependent variable. Ban_{94} is a binary variable indicating the ban, taking value one when the year is greater than 1994 and zero otherwise. Dye_{ij} is a firm level binary variable, which takes a value 1 if a firm belongs to the category "20114" (5-digit NIC 2008) i.e. – *Manufacture of dyes and pigments from any source in basic form or as concentrate*". We use the chemical industry minus the dye-producing firms as the control group. 'Firm Controls' include age, age squared, size (assets) and technology adoption expenditure (except for columns (1) – (4)) of a firm. Numbers in the parentheses are robust standard errors clustered at the 5-digit industry level. ***, **, * denotes statistical significance at 1%, 5%, and 10%.

Table 4: 'Azo-dyes' Ban and Labor Compensation for Upstream (Chemical) Firms: Benchmark Results

	Total Labor Compensation	Managerial Compensation										
		Main Results						Controlling for Other Events				
				Year $\leq$ 1999	IHS	Balanced Panel	Share	Domestic Ban 1997	Import of Finished Goods	1990s Trade Reform		Dye Exports
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\text{Ban}_{94} \times \text{Dye}_{ij}$	–0.017	0.039***	0.028***	0.028***	0.022***	0.177***	0.013***	0.013*	0.038*	0.046***	0.052***	0.038***
	(0.012)	(0.008)	(0.005)	(0.011)	(0.007)	(0.018)	(0.001)	(0.007)	(0.020)	(0.010)	(0.013)	(0.005)
$\text{Ban}_{97} \times \text{Dye}_{ij}$								0.034***				
								(0.007)				
$\text{Dye}_{ij} \times \text{MFGds}_{it-1}$									0.002			
									(0.090)			
$\text{Dye}_{ij} \times \text{Input Tariffs}_{jt-1}$										–0.127**		
										(0.049)		
$\text{Ban}_{94} \times \text{Input Tariffs}_{jt-1}$											–0.009	
											(0.067)	
$\text{Dye}_{ij} \times \text{Exports}_{it-1}$												0.005
												(0.007)
Firm Controls	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-Square	0.25	0.43	0.43	0.46	0.43	0.38	0.20	0.43	0.43	0.44	0.43	0.43
N	11,193	11,193	18,802	7,387	11,193	4,222	11,193	11,193	10,624	10,624	10,624	10,624
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry (3-digit)*Year FE	No	No	No	No	No	No	No	No	No	Yes	Yes	No
Industry (4-digit)*Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	Yes

Notes: Column (1) uses total labor compensation of a firm as the dependent variable. Columns (2) — (11) use managerial compensation of a firm as the dependent variable. Ban_{94} is a binary variable indicating the ban, which takes a value one when the year is greater than 1994. Dye_{ij} is a firm level binary variable, which takes the value one if a firm belongs to the category "20114" (5-digit NIC 2008) that is – *Manufacture of dyes and pigments from any source in basic form or as concentrate*". Ban_{97} is a binary variable indicating the ban in India, which takes the value one when the year is greater than 1997 and takes the value zero otherwise. $MFGds$ is import of finished goods or final products. $Exports$ is the total exports of a firm. $InputTariffs$ is input tariffs at 4-digit industry level. All the regressions concerning input tariffs also contains the same interaction terms with $OutputTariffs$. We use the chemical industry minus the dye-producing firms as the control group. 'Firm Controls' include age, age squared, size (proxied by assets) and the expenditure on technology adoption of the firms. Numbers in the parentheses are robust standard errors clustered at the 5-digit industry level. ***, **, * denotes statistical significance at 1%, 5%, and 10%.

Table 5: 'Azo-dyes' Ban and Labor Compensation for Upstream (Chemical) Firms: Price vs. Quantity

	Number of Total Managers	Average Wage of Managers	Non-Managerial Component	
			Number	Compensation
	(1)	(2)	(3)	(4)
$\text{Ban}_{94} \times \text{Dye}_{ij}$	0.174***	0.083***	–0.268***	–0.029***
	(0.046)	(0.018)	(0.048)	(0.010)
Firm Controls	Yes	Yes	Yes	Yes
R-Square	0.59	0.42	0.70	0.29
N	1,518	1,518	1,518	11,193
Firm FE	Yes	Yes	Yes	Yes
Industry (4-digit)*Year FE	Yes	Yes	Yes	Yes

Notes: Column (1) uses number of managers, column (2) average wage of managers, column (3) number of non-managers, and column (4) non-managerial compensation as the dependent variable, respectively. Ban_{94} is a binary variable indicating the ban, which takes a value one when the year is greater than 1994. Dye_{ij} is a firm level binary variable, which takes a value one if a firm belongs to the dye-producing sector. We use the chemical industry minus the dye-producing firms as the control group. Firm Controls include age, age squared, size (proxied by assets) and the expenditure on technology of the firms. Numbers in the parentheses are robust standard errors clustered at the 5-digit industry level. ***, **, * denotes statistical significance at 1%, 5%, and 10%.

Table 6: Tracing out the mechanism: Product Portfolio

	Product Exit	Product Entry	Core Product	Product Scope	Sales Share	Change in Sales Share	Quantity Sold	Product Quality
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\text{Ban}_{94}\times \text{Dye}_{ij}$	0.048***	0.010***	0.078***	–0.111***	–0.021***	–0.043***	0.146***	0.212***
	(0.003)	(0.003)	(0.009)	(0.038)	(0.002)	(0.011)	(0.068)	(0.036)
$\text{Ban}_{94}\times \text{Dye}_{ij}\times \text{Core}_{ip}$				–0.072***	0.038***	0.121***		
				(0.012)	(0.012)	(0.016)		
Core_{ip}				–0.066***	0.561***	0.569***		
				(0.012)	(0.019)	(0.029)		
R-Square	0.04	0.29	0.16	0.91	0.76	0.33	0.82	0.82
N	33,972	33,972	32,835	33,949	28,586	24,241	32,503	32,503
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	No	Yes	Yes	Yes	Yes	Yes
Product FE	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Industry (4-digit)*Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Columns (1) – (8) use product exit, product entry, core product, product scope (number of varieties produced), sales share of each product, change in sales share, product quality, and quantity sold by a firm as the dependent variable, respectively. In case of product exit (column 1), product entry (column 2), and core product (column 3) we run probit specifications; marginal effects are reported. In case of product exit, the variable takes a value 1 if we do not observe a product in the following year in the sample. In case of product entry, the variable takes a value 1 when a new product appears in the sample. In case of core product, it takes a value 1 if a product is a core product of a firm. We label a product as a core product of a firm if the average sales of the product (over the years 1990-2003) is greater than 70% of the total sales of a firm (across its all products). Ban_{94} is a binary variable indicating the ban, which takes a value 1 when the year is greater than 1994. Dye_{ij} is a firm level binary variable, which takes a value 1 if a firm belongs to the category "20114" (5-digit NIC 2008) that is– *Manufacture of dyes and pigments from any source in basic form or as concentrate*. We use the chemical industry minus the dye-producing firms as the control group. 'Firm Controls' include age, age squared, size (proxied by assets) and the expenditure on technology adoption of the firms. Columns (4), (5), and (6) also contain all the other double interaction terms. Numbers in the parentheses are robust standard errors clustered at the 5-digit industry level. ***, **, * denotes statistical significance at 1%, 5%, and 10%.

Table 7: Tracing out the Mechanism: Factors of Production

	Managerial Compensation				
	Core Product	R&D Expenses	Technology Transfer	Import of Intermediates	Capital Employed
	(1)	(2)	(3)	(4)	(5)
$\text{Ban}_{94} \times \text{Dye}_{ij}$	–0.096***	0.019**	0.039***	0.019**	0.029***
	(0.015)	(0.008)	(0.008)	(0.007)	(0.008)
$\text{Ban}_{94} \times \text{Dye}_{ij} \times \text{Core}_{ip}$	0.134***				
	(0.013)				
$\text{Ban}_{94} \times \text{Dye}_{ij} \times \text{R\&D}_{i}$		0.082*			
		(0.047)			
$\text{Ban}_{94} \times \text{Dye}_{ij} \times \text{TechTransfer}_{i}$			–0.127		
			(0.104)		
$\text{Ban}_{94} \times \text{Dye}_{ij} \times \text{MProdUnits}_{i}$				0.056***	
				(0.015)	
$\text{Ban}_{94} \times \text{Dye}_{ij} \times \text{CapEmp}_{i}$					–8.78e-06
					(0.000)
Firm Controls	Yes	Yes	Yes	Yes	Yes
R-Square	0.75	0.43	0.43	0.43	0.43
N	34,133	11,193	11,193	11,193	11,193
Firm FE	Yes	Yes	Yes	Yes	Yes
Industry (4-digit)*Year FE	Yes	Yes	Yes	Yes	Yes

Notes: Columns (1) – (5) uses total managerial compensation of a firm as the dependent variable. Ban_{94} is a binary variable indicating the ban, which takes a value 1 when the year is greater than 1994. Dye_{ij} is a firm level binary variable, which takes a value 1 if a firm belongs to the category "20114" (5-digit NIC 2008) that is – *Manufacture of dyes and pigments from any source in basic form or as concentrate.* $Core_{ip}$ takes a value 1 if for the core product of a firm. A product is defined as the core product of a firm if the average sales of the product (over the years) is greater than 70%. $R\&D_i$, $TechTransfer_i$, $MProdUnits_i$, and $CapEmp_i$ are binary variables which takes a value 1 if a firm has a positive value of R&D expenses, technology transfer, import of intermediates (raw materials + capital goods), and capital employed. We use the chemical industry minus the dye-producing firms as the control group. All the regressions control for other double interaction terms as well. 'Firm Controls' include age, age squared, size (proxied by assets) and the expenditure on technology adoption of the firms. All the regressions control for all the other required double interaction terms. Numbers in the parentheses are robust standard errors clustered at the 5-digit industry level. ***, **, * denotes statistical significance at 1%, 5%, and 10%.

Table 8: 'Azo-dyes' Ban and Managerial Compensation for Upstream (Chemical) Firms: Tracing Out the Mechanism – Dis-aggregating the Compensation

	Wages		Incentives	
	Managers'	Non-managers'	Managers'	Non-managers'
	(1)	(2)	(3)	(4)
$\text{Ban}_{94} \times \text{Dye}_{ij}$	0.060***	0.045	–0.009	–0.040***
	(0.004)	(0.035)	(0.007)	(0.010)
Firm Controls	Yes	Yes	Yes	Yes
R-Square	0.24	0.57	0.21	0.51
N	11,193	11,193	11,193	11,193
Firm FE	Yes	Yes	Yes	Yes
Industry (4-digit)*Year FE	Yes	Yes	Yes	Yes

Notes: Columns (1) and (2) uses managerial and non-managerial wages; columns (3) and (4) uses managerial and non-managerial incentives of a firm as the dependent variable. Ban_{94} is a binary variable indicating the ban, which takes a value one when the year is greater than 1994. Dye_{ij} is a firm level binary variable, which takes a value one if a firm belongs to "20114" (5-digit NIC 2008) – *Manufacture of dyes and pigments from any source in basic form or as concentrate*". We use the chemical industry minus the dye-producing firms as the control group. 'Firm Controls' include age, age squared, size (proxied by assets) and the expenditure on technology of the firms. Numbers in the parentheses are robust standard errors clustered at the 5-digit industry level. ***, **, * denotes statistical significance at 1%, 5%, and 10%.

Table 9: 'Azo-dyes' Ban and Firm Performance: Upstream (Chemical) Firms

	Total Sales	Exports	Profits after Tax	Total Factor Productivity
	(1)	(2)	(3)	(4)
$\text{Ban}_{94} \times \text{Dye}_{ij}$	0.013	0.039	–0.049*	0.089**
	(0.023)	(0.027)	(0.028)	(0.036)
R-Square	0.89	0.75	0.85	0.81
N	11,193	11,193	10,217	11,159
Firm Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Industry (4-digit)*Year FE	Yes	Yes	Yes	Yes

Notes: Columns (1) – (4) use total sales, exports, profits after tax, and total factor productivity (TFP) of a firm, respectively as the dependent variable. TFP of a firm is measured using Levinsohn and Petrin (2003). Ban_{94} is a binary variable indicating the ban, taking value one when the year is greater than 1994 and zero otherwise. Dye_{ij} is a firm level binary variable, which takes a value 1 if a firm belongs to the category "20114" (5-digit NIC 2008) i.e. – *Manufacture of dyes and pigments from any source in basic form or as concentrate*". We use the chemical industry minus the dye-producing firms as the control group. 'Firm Controls' include age, age squared, size (assets) and technology adoption expenditure of a firm. Numbers in the parentheses are robust standard errors clustered at the 5-digit industry level. ***, **, * denotes statistical significance at 1%, 5%, and 10%.

Table 10: 'Azo-dyes' Ban and Downstream (Leather and Textile) Firms: Falsification Tests

	Mechanisms					Effect			
	Raw Materials		Product Space		R&D	Managerial Compensation			
	Domestic	Imported	Total	Core	Expenses		IHS	Domestic Ban	Share
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\text{Ban}_{94} \times \text{LT}_{ij}$	0.052***	–0.018*	–0.039	–0.058	–0.047**	–0.007	–0.004	–0.0003	0.001
	(0.020)	(0.010)	(0.035)	(0.039)	(0.019)	(0.005)	(0.004)	(0.005)	(0.001)
$\text{Ban}_{97} \times \text{LT}_{ij}$								–0.012***	
								(0.004)	
R-Square	0.93	0.67	0.85	0.14	0.68	0.42	0.42	0.42	0.42
N	91,649	91,649	164,086	167,256	91,650	91,650	91,650	91,650	91,650
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Product FE	No	No	Yes	Yes	No	No	No	No	No
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry (2-digit)*Year Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Columns (1) – (5) uses total expenditure on use of domestic raw materials, imported raw materials, total products produced, core product, expenditure on R&D, respectively as the dependent variables. Columns (6) – (9) use managerial compensation as the dependent variable. Ban_{94} is a binary variable indicating the ban, which takes a value 1 when the year is greater than 1994. Ban_{97} is a binary variable, which takes a value 1 when the year is greater than 1997. LT_{ij} is a firm level binary variable, which takes a value 1 if a firm belongs to "13, 14, and 15" (2-digit NIC 2008) that is – *Manufacture of textiles, wearing apparel, and leather products.* Core product takes a value 1 if a product is a core product of a firm. We label a product as a core product of a firm if the average sales of the product (over the years 1990-2003) is greater than 70% of the total sales of a firm (across its all products). We use rest of the manufacturing sector (less chemical industry) as the control group. In case of core product (column 4) we run probit specification; marginal effect is reported. 'Firm Controls' include age, age squared, size (proxied by assets) and expenditure on technology adoption (except for column (5)) of a firm. Numbers in the parentheses are robust standard errors clustered at the 2-digit industry level. ***, **, * denotes statistical significance at 1%, 5%, and 10%.

Appendix

(FOR ONLINE PUBLICATION)

A Dataset

Our dataset consists of an annual panel of 350 Indian chemical firms across 36 sub-categories of industries (5-digit classification according to NIC 2008), over the time period of 1989–2002. Among these 5-digit industries, a dye-producing firm belongs to the 5-digit classification (according to NIC 2008) "20114" that is – *Manufacture of dyes and pigments from any source in basic form or as concentrate.* There are about 150 dye-makers in our sample. This is our treated group of firms and we use other chemical firms, (that is, chemical firms except the dye-producing ones), as the control group.

We use data from the PROWESS database maintained by the Centre for Monitoring Indian Economy (CMIE). The dataset measures all monetary-based variables in Millions of Indian Rupees (INR) and in order to account for inflation, all variables are deflated by 2005 industry-specific Wholesale Price Index (WPI).

Variable Definitions

(1) **Total labor Compensation**: It is the sum of managerial and non-managerial compensation.

(2) **Managerial Compensation**: It is defined as the total managerial compensation of a firm. This is the sum of middle and top managers' compensation.

(3) **Non-managerial Compensation**: It is the compensation for the non-managers. Non-managers are the ones who do not manage other employees of a firm. Similarly, for wages and incentives.

(4) **Innovation Expenditure**: It is defined as the sum of expenditure on R&D and Royalty Payments for Technical Knowhow, for a given firm.

(5) **R&D Expenditure**: It is defined as the total expenditure on research and development (R&D) of a firm.

(6) **Technology Transfer**: It is defined as the total expenditure on the royalty payments for foreign technical knowhow of a firm.

(7) **Capital Employed**: It is defined as the total amount of capital employed by a firm in its production process.

(8) **Raw Material Expenditure**: It is defined as the total expenditure on raw materials used from domestic sources.

(9) **Product Scope**: It is defined as the total number of product varieties produced by a firm.

(10) **Product Entry**: It is the probability of a new product introduced by a firm.

(11) **Product Exit**: It is the probability of a product dropped by a firm.

(12) **Import of Raw Materials**: It is defined as the total amount of raw materials imported by a firm.

(13) **Import of Capital Goods**: It is defined as the total amount of capital goods imported by a firm.

(14) **Productivity**: Firm-level productivity is estimated using Levinsohn and Petrin (2003) methodology.

(15) **Age**: It is defined as the age of a firm in years.

(16) **Real Assets**: It is the total assets by a firm corrected for inflation using Wholesale Price Index (WPI). This acts as a proxy for size.

(17) **Skill Intensity**: It is defined as the share of non-production workers to the total employees at 3-digit level of 2004 NIC (National Industrial Classification).

(18) **Input Tariffs**: Input tariffs at 4-digit level of 2004 NIC.

B Tables

Table B1: Descriptive Statistics (Chemical Firms)

	Mean	Median	Min	Max
Dependent Variables: Labor				
Total Compensation	78.08	11.50	120.20	5,811.20
Total Managerial Compensation	3.48	0.90	0.10	1,084.30
Non-Managerial Compensation	45.34	1.80	73.20	5,735.20
Managerial Compensation/Total Compensation	0.171	0.088	0.0004	0.571
Managers' Wages	1.27	0.50	0.10	46.80
Managers' Incentives	0.815	0.10	0.10	70.60
Non-Managerial Wages	86.14	12.85	0.10	5,811.20
Non-Managerial Incentives	19.96	3.05	0.10	551.5
Number of Managers	3.47	4	1	16
Number of Non-Managers	463.98	323.50	75	3,428
Dependent Variables: Others				
Innovation Expenditure	21.34	4.10	0.10	2,712.80
R&D Expenditure	21.36	4.10	0.10	2712.80
Technology Transfer	6.18	1.50	0.10	31.50
Capital Employed	1,032.05	178.20	14.20	77,076.40
Raw Material Expenditure	558.41	133.45	0.10	33,608.70
Product Scope	10.96	8	1	55
Product Entry	0.201	0	0	1
Product Exit	0.104	0	0	1
Sales Share$_{CoreProduct}$	0.219	0.060	0	1
Quantity Sold	121,292.60	306	0.01	3.80e+08
Firm Characteristics Variables:				
Age	15.93	11	1	101
Real Assets	1,793.31	313.85	0.102	103,048
Productivity (TFP)	0.833	0.693	0.0006	4.61
Import of Raw Materials	214.78	31.70	0.10	9,526.40
Import of Capital Goods	54.16	4.1	0.10	3,559.60
Industry Characteristics Variable:				
Skill Intensity	0.326	0.327	0.209	0.367
Input Tariffs (%)	86.83	49.91	23.30	202.02

Notes: 'Total Compensation' is the sum of managerial and non-managerial compensation. 'Total Managerial Compensation' is the compensation of all the managers. 'Non-Managerial Compensation', 'Non-Managerial Wages', and 'Non-Managerial Incentives' is the compensation, wages, and incentives for non-managers. 'Managers' Wages' and 'Managers' Incentives' are total managerial wages and incentives, respectively. 'Number of Managers' and 'Number of Non-Managers' is the total number of managers and non-managers in a firm. 'Innovation Expenditure' is the sum of R&D Expenditure and royalty payments for technical knowhow. 'R&D Expenditure' and 'Technology Transfer' are R&D expenditure and royalty for technical knowhow of a firm, respectively. 'Capital Employed' is capital employed by a firm. 'Raw Material Expenditure' is the total raw material expenditure of a firm from domestic sources. 'Product Scope' is the total number of product varieties produced by a firm. 'Product Entry' and 'Product Exit' is the probability of product entry and exit of a firm, respectively. 'Quantity Sold' is the physical amount of quantity sold by a firm. 'Age' is the age of a firm. 'Real Assets' is the total assets of a firm corrected for inflation. 'Productivity (TFP)' is the productivity estimate of a firm as defined by Levinshon-Petrin methodology (Levinsohn and Petrin, 2003). 'Import of Raw Materials' and 'Import of Capital Goods' is the amount of raw materials and capital goods imported by a firm, respectively. 'Skill Intensity' is the ratio of non-production workers to total employees. It is defined at 3-digit NIC level. This data is sourced from the Annual Survey of Industries (ASI). 'Input Tariffs' is the input tariffs faced by a firm. It is defined at 4-digit NIC level. This data is sourced from Chakraborty and Raveh (2018). '$SalesShare_{CoreProduct}$' is the sales share for the core product of a firm. All the variables (except number of managers, number of non-managers, product scope, product entry, product exit, quantity sold, age, productivity estimates, skill intensity, and input tariffs) are expressed in INR Millions.

Table B2: Summary Statistics: Innovation Expenditure and Labor Compensation (Total, Managerial and Non-managerial): Pre- and Post-1994 'Azo-dyes' Ban

	Pre-ban	Post-ban	Pre-ban	Post-ban
	(1)	(2)	(3)	(4)
Panel A: Upstream Firms	Dye-producing		Other Chemical	
Innovation Expenditure	2.71	5.47***	1.61	4.82***
R&D Expenditure	0.65	2.57***	0.39	2.34***
Technology Transfer	2.05	3.00**	1.21	2.49***
Total Compensation	6.16	5.71	9.99	8.64
Managerial Compensation	0.30	0.41**	0.46	0.51
Non-managerial Compensation	5.94	5.39	9.65	8.29
Panel B: Downstream Firms	Leather and Textile		Other Manufacturing	
Innovation Expenditure	0.13	0.46**	0.90	4.12***
R&D Expenditure	0.05	0.19**	0.39	2.10***
Technology Transfer	0.08	0.28**	0.51	2.02***
Total Compensation	6.80	6.82	7.92	8.87*
Managerial Compensation	0.26	0.25	0.34	0.35
Non-managerial Compensation	6.60	6.63	7.66	8.69

Notes: Numbers shows average value for a firm in Millions of Indian Rupees (INR). 'Pre-ban' time frame refers to 1989 – 1994; 'Post-ban' time frame refers to 1995 – 2002. Innovation Expenditure (aggregated over expenditure on R&D and Technology Transfer). A dye-producing firm refers to "20114" (Manufacture of dyes and pigments from any source in basic form or as concentrate) of 5-digit NIC 2008. Other Chemical firms belong to other 5-digit codes of the 2-digit code 20 (NIC 2008), which is the "Chemical Industry". A leather and textile firm belongs to 13, 14, and 15 of 2-digit NIC 2008. Other manufacturing is less textile, leather, and chemical firms. **, * denotes statistical significance at 5%, and 10%, respectively.

Table B3: 'Azo-dyes' Ban and Managerial Compensation for Upstream (Chemical) Firms: Firm Characteristics

	Managerial Compensation				
	Size	Ownership		End-use	
		Domestic	Foreign	Final	Intermediate
	(1)	(2)	(3)	(4)	(5)
$\text{Ban}_{94} \times \text{Dye}_{ij}$	–0.010	0.023***	0.247*	0.009	0.033***
	(0.010)	(0.005)	(0.152)	(0.027)	(0.005)
$\text{Ban}_{94} \times \text{Dye}_{ij} \times \text{Qr}_2$	0.039***				
	(0.014)				
$\text{Ban}_{94} \times \text{Dye}_{ij} \times \text{Qr}_3$	0.056***				
	(0.011)				
$\text{Ban}_{94} \times \text{Dye}_{ij} \times \text{Qr}_4$	0.060**				
	(0.026)				
Firm Controls	Yes	Yes	Yes	Yes	Yes
R-Square	0.24	0.43	0.44	0.43	0.42
N	11,193	10,253	932	3,946	6,282
Firm FE	Yes	Yes	Yes	Yes	Yes
Industry (4-digit)*Year FE	Yes	Yes	Yes	Yes	Yes

Notes: Columns (1) – (5) use total managerial compensation of a firm as the dependent variable. Ban_{94} is a binary indicating the ban, which takes a value 1 when the year is greater than 1994. Dye_{ij} is a firm level binary variable, which takes a value 1 if a firm belongs to "20114 (5-digit NIC 2008) – Manufacture of dyes and pigments from any source in basic form or as concentrate". Quartiles are based on total assets of a firm. If a firm's assets is below the 25th percentile of the total assets of the corresponding industry, it is classified as 1st quartile, and so on. We use the chemical industry minus the dye-producing firms as the control group. 'Firm Controls' include age, age squared, size (assets) and technology adoption expenditure of a firm. Columns (1) and (2) control for the other required double interaction terms. Numbers in the parentheses are robust standard errors clustered at the 5-digit industry level. ***, **, * denotes statistical significance at 1%, 5%, and 10%.

C Graphs

Figure C1: Exports of Leather & Textile Products by India to the World and EU)

Note: Numbers represent total exports (USD million) in a year by India towards the World and European Union (EU). Source: Chakraborty (2017)