DOES MANAGEMENT MATTER? EVIDENCE FROM INDIA

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Abstract:
A long standing question in social science is whether management matters. Certainly management differs across firms, as does performance. However, perhaps every firm chooses its management practices optimally, so that differences across firms simply reflect differences in their environments. To investigate this we run a field experiment on large Indian textile firms to evaluate the causal impact of modernizing their management practices. We do this by providing free management consulting to a set of randomly chosen treatment plants, and compare their performance to a set of control plants. We find that improved management practices led to significantly higher efficiency and quality, and lower inventory levels. These changes increased the average plant's productivity by about 15% and profitability by about \$0.5m (24%) per year. Firms also transferred these improved management practices from their treated plants to other plants within their group. Since firms adopted these profitable management practices this raises the question of why they had not done so before. Our results suggest that informational barriers were initially important in explaining this lack of adoption. Modern management practices are a type of technology that diffuses slowly between firms. In the longer run, constraints around CEO ability and behavior are also important.

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I INTRODUCTION

Economists have long puzzled over why there are such astounding differences in productivity between firms and across countries. For example, US plants in very homogeneous industries like cement, block-ice, white-pan bread and oak flooring display 100% productivity spreads between the 10^{th} and 90^{th} percentile (Syversson 2004, Foster, Haltiwanger and Syverson, 2008). At the country level, Hall and Jones (1999) and Jones and Romer (2009) show how the stark differences in productivity across countries account for a substantial fraction of the differences in per capita income. Understanding the source of these differences is clearly a central issue for economics, as well as many other disciplines in social science.

A natural explanation for these productivity differences lies in variations in management practices. Indeed, the idea that "managerial technology" determines the productivity of inputs goes back at least to Adam Smith's pin factory, and is central to the Lucas (1978) model of firm size. Yet while management has long been emphasized by the media, business schools and policymakers, models of growth and productivity by economists have typically ignored management, reflecting skepticism in the economics profession about its importance.

One reason for this skepticism is the inherent fuzziness of the concept, making it hard to measure and quantify management.[1] Yet recent work has moved beyond the emphasis on the "soft skill" attributes of good managers or leaders such as charisma, ingenuity and the ability to inspire – which can be difficult to measure, let alone change – towards a focus on specific management practices which can be measured, taught in business schools or by consultants, adopted by firms and transferred to other managers. Examples of such practices include key principles of Toyota's "lean manufacturing," the implementation of systems for regular maintenance and repair of machines, continual analysis and refinement of quality control procedures, inventory management and planning, and human resource practices such as performance-based incentives. Ichniowski, Prennushi and Shaw (1998), and Bloom and Van Reenen (2007) measure many of these management practices and find large variations across establishments, and a strong association between better management practices and higher productivity.[2]

But a second problem remains. Can these differences in management explain variations in productivity, or are they simply a reflection of different market conditions? For example, are firms in developing countries not adopting quality control systems because wages are so low that repairing defects is cheap? Without evidence on the causal impact of management practices on performance it is impossible to quantify the impact of management practices on performance, or even say if "bad management" exists at all.

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[1] Lucas (1978, p. 511) notes that in his model "it does not say anything about the tasks performed by managers, other than whatever managers do, some do it better than others".

[2] In related work, Bertrand and Schoar (2003) use a manager-firm matched panel and find that manager fixed effects matter for a range of corporate decisions. They do not explicitly measure the management practices carried out by these managers, but do identify differences in the patterns of managerial decision-making which they call "styles" of management. Lazear and Oyer (2009) provide an extensive survey of the literature.

This paper seeks to provide the first experimental estimates of the importance of management practices in large firms. We use a randomized consulting design and collect unique time-series data on management practices and firm performance. The field experiment takes a group of large multi-plant Indian textile firms and randomly allocates their plants to management treatment and control groups. Treatment plants received five months of extensive management consulting from a large international consulting firm, which diagnosed areas for improvement in core management practices in the first month, followed by four months of intensive support in implementation of these recommendations. The control plants received one month of diagnostic consulting, provided only in order to collect performance data from them.

The treatment intervention introduced modern management practices for factory operations, inventory control, quality control, human resources, planning and sales and order management. We found this management intervention led to significant improvements in quality, lower inventory levels and higher production efficiency. We estimate the interventions to have increased productivity by about 15% and profitability by $500,000 per year (about 24%). Longer run impacts of good management on productivity and profitability should be much larger, because our numbers focus only on short-run changes in a very narrow set of management practices. For example, firms do not change their production manning levels, investment schedules or product mix in the experiment. Firms also spread these management improvements from their treatment plants to other plants within the same group. This provides revealed preference evidence on their beneficial impact.

The improvements were substantial because our sample of firms had very poor management practices prior to the consulting intervention. Most of them had not adopted basic procedures for efficiency, inventory or quality control that have been commonly used for several decades in comparable European, US and Japanese firms. Our results suggest that the lack of these modern management practices is a major reason for the lower average productivity of larger Indian manufacturing firms. Since these practices do not typically require any capital expenditure, and were introduced with the help of the consulting firm during the five-month intervention period, this raises the question of why these profitable management practices had not been previously adopted.

Our evidence suggests that one important factor is informational constraints – Indian firms are simply not aware of the many modern management practices that are common in Western and Japanese firms. Management practices evolve over time, with innovations like Taylor's “Scientific Management”, Ford's mass production, Sloan's M-form corporation, Demming's quality movement, and Toyota's “lean production”. These management technologies spread slowly across firms and countries – for example, the US automotive industry took two decades to adopt Japanese lean manufacturing. We find our Indian firms are far from the management technological frontier and often have little or no exposure to modern management practices that are now standard in the US, Japan and Europe.

Another important factor was the directors’ procrastination and/or prior beliefs that impeded the adoption of better management practices. All our firms were family owned and managed, so that there was a wide distribution of managerial talent amongst the firm's directors. In several cases, the directors repeatedly cited intent to introduce profitable management practices but had not found time to make the changes. In other cases, different directors disagreed whether improving management practices would pay off, and/or broader family squabbles among directors led to paralysis in decision making.

A related question is why product market competition did not drive these badly managed firms out of business? One reason is the reallocation of market share to well managed firms is restricted by span of control constraints on firm growth. In every firm in our sample only members of the owning family are in senior managerial positions. Non-family members are given junior managerial positions whose power is limited to making non financial decisions. The reason is that family members are worried about non-family members stealing from the firm. For example, they worry if they let their plant managers run procurement they might buy yarn at inflated rates from friends and receive kick-backs.

As a result of this inability to decentralize every factory requires a trusted family member to manage it. This means firms can only expand if male family members are available to take up plant manager positions. Thus, by far the best predictor of firms size in our sample was the number of male family members. All the biggest multi-plant firms had multiple brothers, while the best managed firm had only one plant because the founder had no brothers or sons. Hence, well managed firms do not generally grow large and drive unproductive firms out from the market. This helps to explain the lack of reallocation in China and India (Hsieh and Klenow, 2009a) and the centralization of control in firms in developing countries (Bloom, Sadun and Van Reenen, 2009). Furthermore, entry is also limited by the large financing costs for starting a textile firm (our firms have an average of \$13m of assets). So badly run firms are not rapidly driven out of the market.

This paper relates to several strands of literature. First, there is the extensive productivity literature which reports large spreads in total-factor productivity (TFP) across plants and firms in dozens of developed countries. From the outset this literature has attributed much of this spread to differences to management practices (Mundlak, 1961), but problems in measurement and identification has made this hard to confirm (Syversson, 2010). This dispersion in productivity appears even larger in developing countries (Banerjee and Duflo, 2005, and Hsieh and Klenow, 2009a). But, despite this there are still very few experiments on productivity in firms (McKenzie, 2009), and none involving the type of large multi-plant firms studied here.

Second, our paper builds on the literature on the management practices of firms. This has a long debate between the "best-practice" view that some management practices are routinely good and would benefit all firms to adopt these (Taylor, 1911), and the "contingency view" that every firms is already adopting optimal practices but these are different for every firm (Woodward, 1958). The empirical literature trying to distinguish between these views has traditionally been case-study based, making it hard to distinguish between the different explanations and resulting in little consensus in the empirical management literature.[3]

[3] See Gibbons and Roberts (2009) and Bloom, Sadun and Van Reenen (2010) for surveys of this literature.

Third, very recently a number of other ongoing field experiments (for example Karlan and Valdivia, 2010, Bruhn et al. 2010 and Drexler et al. 2010) have begun to estimate the impact of improving business practices in microenterprises in developing countries. This work focuses on basic business training for the owners of these microenterprise, such as separating business and personal finances, basic accounting, and pricing. It generally finds significant effects of these business skills on performance. Taken together with our evidence of substantial impacts of management practices in large firms, this suggests that, first, even in the very smallest firms management matters, and second, that as firms grow management becomes increasingly important as their operations become more complex.

The paper is organized as follows. Section II discusses the Indian textile industry and why we chose this country and industry for our experiment; section III discusses the management intervention; section IV discusses the impact of the management changes on firm performance, while section V discusses the reasons for the existence and persistence of bad management practices in Indian firms. Finally, section VI concludes.

II MANAGEMENT IN THE INDIAN TEXTILE INDUSTRY

II.A. Why work with firms in the Indian textile industry?

Despite rapid growth over the past decade, India's one billion population still has a per-capita GDP in PPP terms of only one-seventeenth of the United States. Labor productivity is only 15 percent of that in the U.S. (McKinsey Global Institute, 2001). While average levels of productivity are low, most notable is the large variation in productivity, with a few highly productive firms and a long tail of low productivity firms (Hsieh and Klenow, 2009a).

Like those in other developing countries for which data is available, Indian firms are typically poorly managed. Evidence from this is seen in Figure 1, which plots results from the Bloom and Van Reenen (2007, 2010) double-blind telephone surveys of manufacturing firms in the US and India. The BVR methodology scores establishments from 1 (worst practices) to 5 (best practices) on specific management practices related to monitoring, targets, and incentives. This yields a basic measure of the use of modern management practices that is strongly correlated with a wide range of firm performance measures like productivity, profitability and growth. The top panel of Figure 1 plots the histogram of these BVR management practice scores for a sample of 751 randomly chosen medium-sized (100 to 5000 employee) US manufacturing firms and the middle panel for Indian ones. The results reveal a thick tail of badly run Indian firms, leading to a much lower average management score (2.65 for India versus 3.33 for US firms). Indian firms tend to not collect and analyze data systematically in their factories and they tend to use less effective target-setting and monitoring and to employ ineffective promotion and reward systems. Bloom and Van Reenen, (2010) show that scores for other developing countries are very similar to those for India. For example Brazil scores 2.69 and China scores 2.64.

India thus appears broadly representative of large developing countries in terms of poor management practices and low levels of productivity. If we are interested in conducting an experiment to improve management, it makes sense to work in a country that is important in of its own right as well as one which contains firms that are broadly representative of firms globally with low initial levels of management quality. India fits the bill.

In order to implement a common set of management practices across firms and measure a common set of outcomes, it is necessary to focus on a specific industry. We chose textile production, since it is the largest manufacturing industry in India, accounting for 22% of manufacturing employment (around 30 million jobs). The bottom panel of Figure 1 shows the BVR management practice scores for textile firms in India, which are similar to those for all Indian manufacturing, with an average score of 2.60.

Within textiles, our experiment was carried out on 20 plants operated by 17 firms in the woven cotton fabric industry. These plants weave cotton yarn into cotton fabric for suits, shirting and home furnishing. They are vertically disintegrated, which means they purchase yarn from upstream spinning firms and send their fabric to downstream dyeing and processing firms. The 17 textile firms involved in the field experiment had an average BVR management score of 2.60, again very similar to the rest of Indian manufacturing.[4] Hence, our sample of 17 Indian firms involved in our management experiment appear broadly similar in terms of management practices to other manufacturing firms in developing countries.[5]

II.B. The selection of firms for the field experiment

The firms we selected operate around Mumbai, which we targeted as a centre of the Indian textile industry (US SIC code 22). The firms were chosen from the population of all public and privately owned textile firms around Mumbai, kindly provided to us by the Ministry of Corporate Affairs (MCA). We supplemented this with member lists from the Confederation of Indian Industry and the Federation of All India Textile Manufacturers Association, creating a list of 1081 firms. From this we kept firms with between 100 to 1000 employees, to yield a sample of 529 firms.[6] We chose 100 employees as the lower threshold because by this size firms require systematic management practices to operate efficiently. We chose 1000 employees as the upper bound to avoid working with conglomerates and multinationals, which would be too large and complex for our intervention to have much impact in the field experiment time-period. Within this group we further focused on firms in the cotton weaving industry (US SIC code 2211) because it was the largest single 4-digit SIC group within textiles. Geographically we focused on firms in the towns of Tarapur and Umbergaon because these two towns provide the largest concentrations of textile firms in the area, and concentrating on two towns substantially reduced travel time for the consultants we employed

[4] None of the differences between the textile sector, the field experiment firms and the rest of Indian manufacturing were statistically significant.

[5] Interestingly, prior work on the Indian textile industry suggested its management practices were also inferior to those in Europe in the early 1900s (Clark, 1987).

[6] The MCA list comes from the Registrar of Business, with whom all public and private firms are required to register on an annual basis. Of course many firms do not register in India, but this is generally a problem with smaller firms, not with 100+ employee manufacturing firms which are too large and permanent to avoid Government detection. The MCA list also provided some basic employment and balance sheet data.

to help the firms. This yielded a sample of 66 potential subject firms with the appropriate size, industry and location for the field experiment.

All of these 66 firms were then contacted by telephone by Accenture, our partnering international consulting firm. Accenture offered free consulting funded by Stanford University and the World Bank as part of a management research project. We paid for the consulting to be provided at no charge to the subject firms to ensure we controlled the intervention. We felt if firms co-paid for the consulting they might have tried to direct the consulting (for example asking for help on marketing or finance), generating a heterogeneous intervention. Moreover, if lack of information about the potential benefits of better management were a factor in inhibiting firms adopting better management practices, we might expect that poorly managed firms might not see ex ante the benefit of such services and so would not be as likely to participate if asked to pay.[7] However, the trade-off may be that firms who have little to benefit from such an intervention or do not really intend to pursue it seriously may choose to take it up when offered for free. We balanced this risk by requiring firms to commit one day per week of senior management time to working with the consultants. This time was required from the top level of the firm in order for changes to be implemented at the operational level. It also was intended to ensure buy-in for the project.

Of this group of firms, 34 expressed an interest in the project, and were given a follow-up visit and couriered a personally signed letter from the US. Of the 34 firms, 17 agreed to commit to senior management time for the free consulting program.[8] We compared the 17 firms taking part in the program with the 49 non-program firms based on the assets data in the MCA database. The 17 program firms were slightly smaller – they had a 8.5% lower level of current assets – although this difference was not statistically significant. We also compared the firms on management practices, measured using the BVR scores, since we had surveyed 31 of the 49 in a textiles-focused survey wave run from Stanford in 2008. Again, we found the firms taking part in the program were not statistically different from the non-program firms, with a tiny BVR management score difference of just 0.032.

The study firms have typically been in operation for 20 years and are family-owned, with some into their second or third generation of family management. They all produce fabric for the domestic market, with many firms also exporting, primarily to the Middle East. Although the intervention took place against the backdrop of the recent global financial crisis, the participating firms do not appear to have been much affected by the crisis. If anything, demand for low grade fabric of the type produced by these plants may have increased somewhat as customers in urban markets traded down, while the textile market in rural India to which this product was usually directed was largely untouched by the crisis.

[7] This may be analogous to Karlan and Valdivia (2009)'s finding that micro-entrepreneurs who expressed less interest in the beginning in business training were the ones who benefited most from it.

[8] The two main reasons for refusing free consulting on the telephone and during the visits was that the firms did not believe they needed management assistance or that it required too much time from their senior management (1 day a week). But it is also possible the real reason is these firms were suspicious of this offer, given many firms in India have tax and regulatory irregularities.

Table 1 reports some summary statistics for the textile manufacturing parts of these firms (many of the firms have other parts of the business in textile processing, retail and even real estate). On average these firms had about 270 employees, current assets of $13 million and sales of $7.5m a year. Compared to US manufacturing firms these firms would be in the top 2% by employment and the top 5% by sales[9], and compared to India manufacturing in the top 1% by both employment and sales (Hsieh and Klenow, 2009b). Hence, by this criterion, as well as by most formal definitions[10], these are large manufacturing firms.

These firms are also complex organizations, with a median of 2 textile plants per firm and 4.4 hierarchical levels from the shop-floor to the managing director. These levels typically comprise the worker, foreman, plant manager and managing director, with about 50% of firms also having an additional level of department manager between the foreman and plant manager. In all the firms, the managing director is the single-largest shareholder, reflecting the lack of separation of ownership and control in Indian firms. All other directors are family members, with no firm having any non-family senior management. One of the firms is publicly quoted on the Mumbai Stock Exchange, although more than 50% of the equity is still held by the managing director and his father.

In exhibits (1) to (9) we include a set of photographs of the plants. These are included to provide some background information to readers on their size, production process and initial state of management. As is clear these are large establishments, with multiple several story buildings per site, and typically several production sites per firm, plus a head office in Mumbai.

III THE MANAGEMENT INTERVENTION

III.A. Why use management consulting as an intervention

The field experiment aimed to improve the management practices of a set of randomly selected treatment plants and compare the performance of these to a set of control plants whose management has not changed (or changed by less). To do this we needed an intervention that improved management practices on a plant-by-plant basis. To achieve this we hired a management consultancy firm to work with our treatment plants to improve their management practices.

We selected the consulting firm using an open tender. The winner was Accenture consulting, a large international management consulting and outsourcing firm. It is headquartered in the U.S. and publicly listed with about 180,000 employees globally, including 40,000 in India.

[9] Dunn & Bradstreet (August 2009) lists 778,000 manufacturing firms in the US with only 17,300 of these (2.2%) with 270 or more employees and only 28,900 (3.7%) with $7.5m or more sales.
[10] Most European countries and international agencies define large firms as those with more than 250+ employees, the US as having 500+ employees, and India as having Rs 5 crore ($1.25 USD+) of revenue.

The senior partners of the firm who were engaged in the project were based in the US, but the full-time consulting team of up to 6 consultants (including the managing consultant) came from the Mumbai office. These consultants were all educated at top US, European or Indian business and engineering schools, and most of them had prior experience working with US and European multinationals. Selecting a high profile international consulting firm substantially increased the cost of the project. But it meant that our experimental firms were more prepared to trust the consultants and accept their advice, which was important for getting a representative sample group. It also offered the largest potential to improve the management practices of the firms in our study, which was needed to understand whether management matters. The project ran from August 2008 until April 2010, and the total cost of this was $US1.2 million, or approximately $700k per treatment firm. This high cost was despite the consultants' charging pro-bono rates (50% of commercial rates) due to our research status, the US partners providing their time for free, and Indian consulting rates being about 1/3 of US rates; equivalent consulting engagements procured on the open market would have cost around $500,000.[11]

While the intervention offered was high-quality management consulting services, the purpose of our study was to use the improvements in management generated by this intervention to understand how much management matters. It was not to evaluate the effectiveness of the international consulting firm. Our treatment effect is the impact on the average firm that would take-up consulting services when offered for free, which is not necessarily the same as the effect for the average or even the marginal client for the consulting firm. The firms receiving the consulting services might change behavior more if they were voluntarily paying for these services, and the consulting company might have different incentives to exert effort when undertaking work for a research project like this compared to when working directly for paying clients. Based on our intensive interaction with the consulting company, including bi-weekly meetings throughout the project, and discussions with the clients, we do not believe the latter to be an important concern, but nevertheless acknowledge that any attempt to extrapolate the findings of this study to discuss the effectiveness of international management consultants faces these issues. In contrast, neither of these issues is an important concern for the central purpose of this experiment: to determine whether and how much management practices matter for firm performance.

III.B. The management consulting intervention

Textile weaving is a four stage process (see Exhibit 2). In the first stage individual threads of yarn are aligned in a pattern corresponding to the fabric design and wound repeatedly around a "warp beam". The warp beam fits across the bottom of a weaving machine and carries the threads that will run vertically. In the second and third stages the warp beam is attached to a drawing stand and then a weaving loom, and the horizontal cross threads woven in. This cross thread is called the weft weave (as opposed to the vertical warp weave). Finally, the fabric is checked for quality defects, and defects repaired wherever possible.

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[11] At the bottom of the consulting quality distribution consultants are extremely cheap in India. At the top end rates are comparable to those in the US and Europe because the consultants they employ are often US or European educated, and have access to international labor markets. In fact 2 of our team of 6 Indian consultants had previously worked in the US for large multinationals, and had chosen to return to India for family reasons.

A typical factory comprises several buildings in one gated compound (see Exhibit 1), operating 24 hours a day for 7 days a week. One building houses the production facilities, comprising 2 warping machines occupying one floor and about 5% of the manpower, about 60 weaving machines occupying another floor and 60% of the manpower, and a large checking and repair section occupying about 20% of the manpower and a third floor. The remaining 15% of the manpower works in the raw materials and finished goods stores which occupy an adjacent building, and in back-office processing, which is typically located in a third building. The combined size of these buildings (typically about 50,000 square feet and 130 employees), is similar to that of a U.S. Wal-Mart or Home Depot retail store. Thus, these organizations are so large that no one person can observe the entire production process, so that formal management systems to collect, aggregate and process information are necessary.

The intervention aimed to improve the management practices of these plants. Based on their prior experience in the textile industry and in manufacturing more generally, the consulting firm identified a set of 38 key management practices on which to focus. These 38 management practices encompass a range of basic manufacturing principles that are standard in almost all US, European and Japanese firms and that the consulting firm believed would be of benefit to the textile firms, and would be feasible to introduce during the intervention period. These 38 practices are listed individually in Table 2, alongside their frequency of adoption prior to the management intervention in the 28 plants owned by our 17 firms, and the frequency of adoption pre and post the intervention in the treatment plants. The baseline adoption rates show a wide dispersion of practices – from 96% of plants who recorded quality defects to 0% of plants initially using scientific methods to define inventory norms[12] with an overall adoption rate of 26.9%. These practices are categorized into 6 broad areas:

- Factory Operations (to increase output): Plants were encouraged to undertake regular maintenance of machines, rather than repairing machines only when they broke. When machine downtime did occur plants were encouraged to record and evaluate this, so they could learn from past failures to reduce future downtime. They were also encouraged to keep the factory floor tidy and organized, both to reduce accidents and to facilitate the movement of materials and goods. Daily posting of performance of individual machines and weavers was suggested to allow management to assess individual and machine performance. Finally, plants were encouraged to organize the machine spares so these could be located in the event of a machine breakdown, and develop scientific methods to define inventory norms for spare parts.

- Quality control (to increase quality and reduce rework hours): Plants were encouraged to record quality defects by major types at every stage of the production process on a daily basis. They were encouraged to analyze these daily to address quality problems

[12] This involves calculating the cost of carrying inventory (interest payments and storage costs) and the benefits of carrying inventory (larger order sizes and lower probability of stock-outs) and using this to define an optimal inventory level. The use of inventory norms is almost universal in US, European and Japanese firms of this size. The consultants – who were used to dealing with Mumbai based multinational firms - were genuinely surprised by the lack of many of these standard types of management practices in these firms.

rapidly, so that the same defect would not repeatedly occur. Standard operating procedures were established to ensure consistency of operations.

- Inventory (to reduce inventory levels): Plants were encouraged to record yarn stocks, ideally on a daily basis, with optimal inventory levels defined and stock monitored against this. Yarn should be sorted, labeled and stored in the warehouse by type and color, and this information logged onto a computer, so yarn can be located when required for production. Yarn that has not been used for 6+ months should be utilized in new designs or sold before it deteriorates.

- Planning (to increase output and to improve due date performance): Plants were encourage to plan loom usage 2 weeks in advance to ensure prepared warp beams are available for looms as needed. This helps to prevent weaving machines lying idle. The sales teams (based in Mumbai) should meet twice a month with the production teams to ensure delivery schedules are matched against the factory's production capacity.

- Human-resource management (to increase output): Plants were encouraged to introduce a performance-based incentive system for workers and managers. The recommended system comprised both monetary and non-monetary incentives (e.g. a radio for the most productive weaver each month). Incentives were also linked to attendance to reduce absenteeism. Job descriptions were defined for all workers and managers to improve clarity on roles & responsibilities.

- Sales and order management (to increase output and to improve due date performance): Plants were encouraged to track production on an order-wise basis to prioritize customer orders with the closest delivery deadline. Design-wise and margin-wise efficiency analysis was suggested so that design-wise pricing could be based on production costs (rather than flat-rate pricing so that some designs sold below cost).

These 38 management practices in Table 2 form a set of precisely defined binary indicators which we can use to measure improvements in management practices as a result of the consulting intervention[13]. The indicators allow for differences in the extent to which a particular system is put in place. For example, in factory operations, a basic practice is to record machine downtime. A second practice is actually to monitor these records of downtime daily, while a third practice is to analyze this downtime and create and implement action plans on a regular (fortnightly) basis in order to act on this information. A general pattern at baseline was that in many cases plants recorded information (often in paper sheets), but had no systems in place to monitor these records or use them to make decisions. Thus, while 93 percent of the treatment plants recorded quality defects before the intervention, only 29 percent monitored them on a daily basis or by the particular sort of defect, and none of them

[13] We prefer these indicators to the BVR management practice score for our work here, since they are all objective binary indicators of specific practices, which are directly linked to the intervention. In contrast, the BVR indicator measures practices at a more general level, with each measured on a 5-point ordinal scale. Nonetheless, the sum of our 38 pre-intervention management practice scores is correlated with the BVR score at 0.404 (p-value of 0.077) across the 17 firms.

had an analysis and action plan based on this defect data – that is, a system to address repeated quality failures.

Indeed we found that while firms usually had historic data of some form on production and quality, it was typically not in a form that was convenient for either them or us to access. The majority of firms had electronic resource planning (ERP) computer systems which they used to record basic factory operation metrics (such as machine efficiency, the share of time a machine is running) on a daily basis. These computer systems were designed by local vendors, and could be used to generate very simple reports that were looked at only on an irregular, ad hoc basis. Generating more detailed reports that went outside these simple reports required extracting the data and using it with other software. Quality records were worse. Firms typically had handwritten logs of defects, which they referred to only when customers complained. Most firms did not frequently monitor inventory levels, at most doing stock takes a few times a year. All this meant that the firms lacked the data needed to measure performance prior to the intervention.

The consulting treatment had three stages. The first stage took one month, and was called the *diagnostic* phase. This involved evaluating the current management practices of each plant and constructing a performance database. The construction of this database involved setting up processes for measuring a range of plant-level metrics – such as output, efficiency, quality, inventory and energy use – on an ongoing basis, plus constructing a historical database from plant records. For example, to facilitate quality monitoring on a daily basis a single metric was defined, termed the Quality Defects Index (QDI), which is a severity-weighted average of the major types of defects. To construct historical QDI values the consulting firm converted the historical quality logs into QDI wherever possible. At the end of the diagnostic phase the consulting firm provided each treatment and control plant with a detailed analysis of their current management practices and performance. The treatment plants were given this diagnostic phase as the first step in improving their management practices. The control plants were given this diagnostic phase because we needed to construct historical performance data for them and help set up systems to generate ongoing data.

The second phase was a four month *implementation* phase which was given only to the treatment plants. In this the consulting firm followed up on the diagnostic report to help implement management changes to address the identified shortcomings. This focused on introducing the key 38 management practices which the plants were not currently using. The consultant assigned to each plant would work with the plant managers to put the procedures into place, fine-tune them, and stabilize them so that they could be readily run by employees. For example, one of the practices implemented was daily meetings for management to review production and quality data. The consultant would attend these meetings for the first few weeks of the implementation phase to help the managers run them, would provide feedback on how to run future meetings, and fine-tune their design to the specific plant's needs. During the rest of the implementation phase the consultant would attend the meetings on a weekly basis to check they were being maintained, and to further fine-tune them. As another example, the consultant would help the plant managers to set up a system for monitoring the aging of yarn stock, and would walk them through the steps needed to ensure old stock was used, sold or scrapped.

The third phase was a *measurement* phase which lasted until the end of the experiment (currently planned to be April 2010). For budgetary reasons this phase involved only three consultants and a part-time manager, and was designed to collect performance and management data from the plants.

So, in summary, the control plants were provided with just the diagnostic phase (totaling 129 consultant hours on average) and the measurement phase, while the treatment plants were provided with the diagnostic and implementation phase (totaling 541 consultant hours on average) as well as the measurement phase. As such our measured impact of the experiment will be an underestimate of the impact of consulting since our control group also had some limited consulting. Nevertheless, by varying the intensity of the treatment we hoped to vary the change in management practices which occur for treatment versus control firms, enabling us to use this variation in management practices to determine the effect of management.

III.C. The experimental design

The design of the experiment was constrained because we worked with large firms. We wanted to work with large firms because their operational complexity means management practices are likely to be particularly important to them, and because they are underrepresented in developing countries. However, providing effective consulting to large firms is expensive. This led to a number of trade-offs:

<u>Sample size:</u>
We worked with a sample of just 20 plants, because we hired international consultants and asked them to provide intensive consulting to each plant. We considered hiring cheaper local consultants and providing a light intervention of few hours a week, which could have yielded a sample of several hundred plants. But two factors pushed against this. First, many large firms in India are reluctant to let outsiders into their plants because of their lack of compliance with tax, labor and health and safety regulations. So to minimize selection bias we wanted to offer a high quality consulting intervention that large firms would value enough to be willing to accept. This would maximize initial take-up (26% as noted in section II.B) and retention (100% as no firms dropped out of the experiment). Second, the consensus from prior discussions with Indian business people was that achieving a measurable impact would require extensive engagement in firms of this size. Changing practices in large firms is complex and time consuming, and they felt we would have little impact with a low-quality light-touch intervention.

A small sample size typically leads to concerns about statistical power. However, we believe that there are several mitigating factors in this instance. First, these are extremely large plants with about 80 looms and about 130 employees so that idiosyncratic shocks – like machine breakdowns or individual illness – tend to average out. As a result changes in plant-level performance tend to reflect more systematic changes in management than micro-level shocks. Second, the data is relatively accurate since it was collected on the firm premises by our international consulting partner rather than from self-reported survey data (as is typically in many firm-level studies). Third, we collect high-frequency (at least weekly) data for each plant, so that to date we have about 1500 plant-week observations on a range of variables from both the pre- and post-intervention periods. Fourth, the sample firms are extremely homogenous in terms of size, industry and region, and so almost all external shocks are common. So that identifying the impact of variations in management on output is easier because time dummies can strip out external shocks. Finally, because the intervention was so intensive the treatment effect was extremely large, as we will show in the next section.

Timing: The consulting intervention had to be initiated in three batches because the 6 person consulting team limited the number of simultaneous interventions that could be launched. So the first wave started in September 2008 with 4 treatment plants. In April 2009 a second wave of 10 treatment plants was initiated, and in July 2009 the last wave of 6 control plants was initiated. This design was selected to start with a small first wave as this initial stage was the most difficult because the consulting team was new and had to fine-tune the methodology. The second wave included all the remaining treatment firms because: (i) the consulting interventions take time to affect performance and we wanted the longest time-window to observe the treatment firms; and (ii) we could not mix the treatment and control firms across waves because of the operation of the intervention process.[14] The third wave therefore contained only control firms. Management and performance data for all firms was collated from April 2008 to April 2010 to enable us to compare firms over a comparable time period.

Relative treatment and control group sizes: We picked 14 treatment plants in two waves and 6 control plants.[15] We picked more treatment than control plants because, first, the staggered initiation of the interventions meant the different groups of treatment plants provided some cross identification for each other, and second, the treatment plants were more useful for trying to understand why firms had not adopted basic management practices before. Trying to change management practices often uncovers any constraints on these practices. For example, control plants all agreed to implement weekly meetings, but few of them actually consistently did this. In the treatment plants we discovered the reason for this was the consultants needed to run the first few meetings to explain the process and develop problem solving protocols.

The treatment and control firms are not statistically different across any of the characteristics we could observe, (see for example Table 1). We also collected data on changes in management practices in the 8 "non-experimental" plants that were owned by one or another of the 17 firms in the study, but that were not part of either the treatment or control group of plants. This was relatively easy to do as it just involved occasional visits to the plants. We did not collect performance data for these plants as this was much more labor intensive and our

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[14] The reason is each wave had a one-day kick-off meeting jointly held with all the firms, which involved presentations from a range of senior partners from the consulting firm. This helped impress the treatment and control firms with the expertise of the consulting firm and highlighted the huge potential for improvements in management. This meeting involved a project outline, which was slightly different for the treatment and control firms because of the different interventions. Since we did not tell firms about the existence of treatment and control groups - only that this was a Stanford and the World Bank project on management in textile firms - we could not mix the treatment and control groups.

[15] These were chosen by randomly picking 6 firms to be in the control group and then randomly picking a plant from each. We randomly picked 14 treatment plants from the remaining 11 firms. This left 8 non-experimental plants, 3 of which were in control firms and 5 of which were in treatment firms.

consulting team did not have the manpower to do this. Thus there were up to 20 plants on which we had performance data and 28 plants on which we had management adoption data.

III.D. The impact of the intervention on plants management practices

In Figure 2 we plot the average management practice adoption of the 38 practices listed in Table 2 for the 14 treatment plants, the 6 control plants and the 5 other plants of the treatment firms. This data is shown at 3 month intervals for April 2008 until April 2009, and 2 month intervals from June 2009 onwards. Data from the intervention phase onwards was compiled from direct observation at the factory. Data from before the intervention phase was collected from detailed interviews of the plant management team based on any changes to management practices during the prior year. Figure 2 shows five key results:

First, the plants in all of the groups started off with low baseline adoption rates of the set of 38 management practices. [16] Among the 28 individual plants the initial adoption rates varied from a low of 7.9% to a high of 55.2%, so that even the best managed plant in the group had in place just over half of the 38 key textile manufacturing management practices. This is consistent with the results on poor general management practices in Indian firms shown in Figure 1. For example, many of the plants did not have any formalized system for recording or improving production quality so that the same quality defect would not arise repeatedly. Most of the plants also had no organized yarn inventories, so that yarn was stored mixed by color and type, without labeling or computerized entry. Consequently, yarn was being ordered despite already being in stock (see also Exhibit 5). The production floor was often blocked by waste, tools and machinery, impeding the flow of workers and materials around the factory (see Exhibits 3-4). Machines often were not routinely maintained, so that they would break down frequently, leading to low efficiency levels. Pricing was not matched against production costs, so that complex designs were charged at the same rate as simple designs because no data was collected on production costs of different designs. This was as surprising to us as to our international consulting firm used to dealing with well managed Indian and foreign multinationals.

Second, the intervention did succeed in changing management practices. The treatment wave 1 and treatment wave 2 plants given the 5 month diagnostic and implementation consulting intervention increased their use of the 38 management practices over the period, raising their adoption rate by 35.2 percentage points on average (an improvement from 32.8% to 68% of practices implemented).

Third, the increase in management practices in the treatment firms occurred gradually over the intervention period. In part this is because it takes time to introduce and stabilize new management practices. Typically the consulting firm would start by explaining the new management practices, then would introduce the procedures, and finally spend time giving feedback and coaching to fine-tune the process. The slow take-up also reflects the time it takes for the consulting firm to gain the confidence of the firm's directors. Initially many directors were somewhat skeptical of the suggested management changes, and only

[16] The difference between the treatment, control and other plant groups is not statistically significant, with a p-value on the difference of 0.248 (see Table 2).

implemented the easiest changes around quality and inventory. Once these started to generate substantial improvements in profits the firms then started to introduce the more complex improvements around operations and HR.

Fourth, the control plants, which were given only the 1 month diagnostic, also increased their adoption of these management practices, but by only 9.3 percentage points on average. This is substantially less than the increase in adoption of the treatment wave, indicating that the four months of the implementation the treatment plants received was important in changing management practices.[17]

Fifth, the non-experimental plants (the other plants in firms with a treatment or control plant) also saw a small increase in the adoption of management practices. In the 5 plants that were in a firm that also included a treatment plant management adoption rates increased by 9.0 percentage points. This was because the firms' managing directors started copying the new management practices from the treatment plants to the other non-experimental plants in their firms. The increase here is much smaller than in the treatment plants themselves, suggesting that only some practices were easily transferred over. The 3 non-experimental plants in the control firms also improved their adoption practices, but by only 4.8 percentage points. This again suggests some of the new practices adopted in control plants were copied over to other plants in the same firm.

To formally test whether the intervention has differentially changed management practices between the treatment and control plants, we use the sample of treatment and control plants to run the following regression for plant *i* at time *t*

$$\text{MANAGEMENT PRACTICE SCORE}_{i,t} = \alpha_i + \beta_t + \lambda \text{TREAT}_{i,t} + \varepsilon_{i,t} \qquad (1)$$

where α_i are plant fixed effects, β_t are calendar month fixed effects, and $\text{TREAT}_{i,t}$ is our management treatment indicator. We consider two specifications for $\text{TREAT}_{i,t}$. The first is to make it a binary indicator of whether the firm has begun the 4-month implementation phase at time *t*. This is zero for all firms before the intervention, and 1 for the treatment group once the implementation treatment begins. In this case λ will measure the average effect of the consulting intervention on management practices in the treatment plants relative to the control plants, averaging over short-run and long-run effects. Second, we enter $\text{TREAT}_{i,t}$ as the number of months since the 4-month implementation phase began in levels and squared (and zero for time periods before the intervention). This will measure the per-month improvement in management practices in the treatment plants relative to the control plants, allowing for a varying rate of adoption over time. This is important because, as Figure 2 highlights, firms have the fastest rate of adoption of management practices early on, slowing down throughout the intervention, and even dropping back later on after the end of the intervention on some cases. So a quadratic time term approximates this adoption curve in management practices.

[17] Much of this 9.3 percentage point increase in the adoption of these management practices in the control firms arose from our requests for data. They started tracking inventory and quality after we requested this data from them, which they were told would be used for research but also to provide them with performance benchmarking.

We bootstrap cluster all standard errors at the firm level (with all results robust to instead clustering at the plant level).

We also consider several measures of the management practice score. The first is our total score, which is the average of the 38 binary practices outlined in Table 1. Second, we look at the individual adoption rates for each of the six groups of management practices listed in Table 2: factory operations, quality control, inventory control, loom planning, human resources, sales and orders. This enables us to delve deeper into which types of management practices have been most affected by the experiment.

Panel A of Table 3 shows the average treatment impacts of the intervention on these management practice scores, while panel B shows the per-month effects which are obtained by using months since treatment in levels and squared as the treatment variable. Looking first at Panel A it is clear that firms have seen big increases across the board in their adoption of management of key textile management practices of the order of a 30 percentage point increase (20 percent versus control firms after including time dummies). The rises in adoption rates have been highest in the practices for improving operations, improving quality and reducing inventory holdings, which are also the areas of the firm we have seen the largest improvements in performance (as shown in section (IV) below). Looking at Panel B there is evidence of a highly significant positive cumulative time and a negative cumulative time squared, suggesting a declining adoption rate.

Most importantly for our study, these results show that the experiment differentially changed management practices between treatment and control plants, providing variation which we can use to examine the impacts of this on plant-level outcomes. In our estimation strategy we use the results with the cumulative intervention in levels and squared because of its greater predictive power for management practices.

IV THE IMPACT OF MANAGEMENT ON PERFORMANCE

The unique panel data on management practices and plant level performance, coupled with the experiment which induces random variation in management practices, enables us to estimate whether management matters. We have a range of plant-level performance metrics, with the key variables being measures of quality, inventories, and production efficiency. This data was recorded at a daily frequency wherever possible, or, if not, at weekly or monthly frequency. Historical data for the period before the intervention was constructed from a range of sources, including firms' Electronic Resource Planning (ERP) computer systems, production logs, accounts and order databases. We aggregate our data to the monthly level to keep the data at the highest level of aggregation.

Previous literature (e.g. Black and Lynch (2001) and Bloom and Van Reenen, (2007)) has shown a strong correlations between management practices and firm performance in the cross-section, with other papers (e.g. Ichniowski et al. 1998) showing this in the panel.[18]

We begin with a panel fixed-effects specification:

$$OUTCOME_{i,t} = \alpha_i + \beta_t + \theta MANAGEMENT\ PRACTICE\ SCORE_{i,t} + \nu_{i,t} \quad (2)$$

The concern is then of course that management practices are not exogenous to the outcomes that are being assessed, even in changes. For example, a firm may only start monitoring quality when it is starting to experience a larger than usual number of defects, which would bias the fixed-effect estimate towards finding a negative effect of better management on quality. Or firms may start monitoring quality as part of a major upgrade in worker quality and equipment, in which case we would misattribute quality improvements arising from better capital and labor to the effects of better management.

To overcome this endogeneity problem, we instrument the management practice score with the cumulative treatment levels and squared terms. We use these cumulative months since the implementation stage began in levels and squared, since Table 3 showed that these had a stronger first-stage than the binary treatment indicator. The exclusion restriction is then that the intervention only affected the outcome of interest through its impact on management practices, and not through any other channel. We believe this assumption is justified, since the consulting firm focused entirely on management practices in their recommendations to firms, and firms did not buy new equipment or hire new labor as a result of the intervention (at least in the short run).[19] The IV estimator will then allow us to answer the headline question of this paper – does management matter?

If the impact of management practices on plant-level outcomes is the same for all plants, then the IV estimator will provide a consistent estimate of the marginal effect of improvements in management practices, telling us how much management matters for the average firm participating in the study. However, if the effects of better management are heterogeneous, then the IV estimator will provide a local average treatment effect (LATE). The LATE will then give the average treatment effect for plants which do change their management practices when offered free consulting. If plants which stand to gain more from improving management are the ones who change their management practices most as a result of the consulting, then the LATE will exceed the average marginal return to management. While it will understate the average return to management if instead the plants that only change management when consulting is provided free are those with least to gain. There was heterogeneity in the extent to which treatment plants changed their practices, with the before-after change in average

[18] Note that other papers using repeated surveys have found no significant panel linkage between management practices and performance (Cappelli and Neumark (2001) and Black and Lynch (2004)), probably because of measurement error issues with repeated surveys. See Bloom and Van Reenen (2010) for a full literature survey.

[19] The exceptions to this were that the firms hired on average \$34 (1,700 rupees) of extra manual labor to help organize the stock rooms and clear the factory floor, spent \$418 (10,900 rupees) on plastic display boards for the factory floor, standard-operating procedure notices and racking for the store rooms, and spent an additional \$800 on salary and prizes (like a radio and a watch) for managerial and non managerial staff. These and any other incidental expenditures are too small to have a material impact on our profitability and productivity calculations.

total management practice score ranging from 21.1% to 58.3%. The feedback from the consulting firm was that to some extent it was firms with the most unengaged, uncooperative managers who changed practices least, suggesting that the LATE may underestimate the average impact of better management if these firms have the largest potential gains from better management. Nonetheless, we believe the LATE estimate to be a parameter of policy interest, since if governments are to employ policies to try and improve management, information on the returns to better management from those who actually change management practices when help is offered is informative.

We can also directly estimate the impact of the consulting services intervention on management practices via the following equation:

$$\text{OUTCOME}_{i,t} = a_i + b_t + c\text{TREAT}_{i,t} + e_{i,t} \qquad (3)$$

The parameter *c* then gives the intention to treat effect (ITT), and gives the average impact of the intervention in the treated plants compared to the control plants. This estimates the effect of giving firms the full implementation phase of the consulting, rather than just the diagnostic phase.

In all cases we include plant and time fixed effects, and bootstrap cluster the standard errors at the firm level. We have daily data on many outcomes, but aggregate them to the weekly level to reduce higher-frequency measurement errors.

IV-A Quality

Our measure of quality is the Quality Defects Index (QDI), a weighted average score of quality defects, which is available for all but one of the plants. Higher scores imply more defects. Figure 3 provides a plot of the QDI score for the treatment and control plants relative to the start of the treatment period. This is September 2008 for Wave 1 treatment, April 2009 for Wave 2 treatment and controls plants.[20] This is normalized to 100 for both groups of plants using pre-treatment data. To generate confidence intervals we also estimate a cubic spline with a knot at the start of the implementation phase, and plot this plus the 95% confidence intervals.[21]

As is very clear the treatment plants started to significantly reduce their QDI scores rapidly from about week 5 onwards, which was the beginning of the implementation phase following the initial 1 month diagnostic phase. As yet the control plants have not shown any downward trend in their QDI scores. These differences in trends between the treatment and control plants are also significant, as indicated by the non-overlapping 95% confidence intervals which were estimated pointwise through block-boostrap on the plants.

[20] Since the control plants have no treatment period we set their timing to zero to coincide with the 10 Wave 2 treatment plants. The maximizes the overlap of the data.

[21] Note that boot strapping the underlying series to obtain *pointwise* confidence intervals is not appropriate for interconnected data series like this. To obtain appropriate *series* confidence intervals we use a non-parametric spline with a knot at the implementation period, and generate the spline confidence intervals by block bootstrap on the plants ((Ai and Chen (2003)).

Table 4 asks whether management practices matter for production quality using a regression approach. In column (1) we present the fixed-effects OLS results which regresses the monthly log(Quality Defects Index) score on plant level management practices, plant fixed effects, and a set of monthly time dummies. The standard errors are boostrap clustered at the firm level to allow for any potential correlation across different experimental plants within the same firm. The coefficient of -0.997 implies that increasing the adoption of management practices by 10 percentage points would be associated with a reduction of 9.97% in the quality defects index.

The reason for this large effect is that measuring defects allows firms to address quality problems rapidly. For example, a faulty loom that creates weaving errors would be picked up in the daily QDI score and dealt with in the next day's quality meeting. Without this the problem would often persist for several weeks since the checking and mending team has no system (or incentive) for resolving defects. In the longer term the QDI also allows managers to identify the largest sources of quality defects by type, design, yarn, loom and weaver, and start to address these systematically. For example, designs with complex stitching that generate large numbers of quality defects can be dropped in exchange for simpler designs. This ability to dramatically improve quality through systematic data collection and evaluation is a key tenet of the highly-successful lean manufacturing system of production (see, for example, Womack, Jones and Roos, 1992).

In Table 4, column (2), we instrument management practices using the experimental intervention to identify the causal impact of better management on quality. Given the results in Table 3 we use the number of months since the intervention began in levels and squared[22] as the instruments for management practices. After doing this we see a significant point estimate of -1.889, suggesting that increasing the management practice adoption rate by 10% would be associated with a reduction in quality defects of 18.9%.

The rise in the point estimate for the IV estimator could be due to measurement error in the underlying management index and/or because firms are endogenously adopting better management practices when their quality starts to deteriorate. There was some anecdotal evidence for the latter, in that the consulting firm reported some plants with improving quality were less keen to implement the new management practices because they felt these were unnecessary. This suggests that the fixed-effects estimates for management and performance in prior work like Ichniowski, Prennushi and Shaw (1997) may be underestimating the true impact of management on performance.

In column (3) we re-estimate our IV specification using only the plants involved in the Wave 2 treatment and the control group as a robustness test. These plants have more similar diagnostic phase start dates (April 2009 and July 2009 respectively). Reassuringly we find very similar results, with in fact a larger (although not significantly so) point estimate.

Finally, in column (3) we look at the intention to treat (ITT), which is the average reduction in the quality defects index in the period after the intervention in the treatment plants versus the

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[22] The cumulative intervention has a value of 1 in month 1 of the intervention, 2 in month 2, 3 in month 3 etc. The cumulative intervention squared have a value of 1 in month 1, 4 in month 2, 9 in month 3 etc.

control plants. We see this is associated with a 34.1% (exp(-.417)-1) reduction in the QDI index.

IV-B Inventory

Table 5 shows the regression results for raw material (yarn) inventory.[23] In all columns the dependent variable is the log of raw materials, so the coefficients can be interpreted as the percentage reduction in yarn inventory. The results are presented for the 18 plants for which we have yarn inventory data. In column (1) we present the fixed-effects results which regresses the monthly yarn on the plant level management practices, plant fixed effects, and a set of monthly time dummies. The standard errors are boostrap clustered at the firm level to allow for any potential correlation across different experimental plants within the same firm. The coefficient of -0.661 says that increasing management practices adoption rates by 10 percentage points would be associated with a yarn inventory reduction of about 6.6%. In Table 5, column (2), we see the impact of management instrumented with the intervention displays a point estimate of -0.749, again somewhat higher than the FE estimates in column (1). In column (3) we look at the coefficient for the wave 2 treatment and control firms only and again see a similar large impact of management practices on inventory levels.

The reason for this effect is that these firms were carrying about 4 months of inventory on average before the intervention, including a large amount of dead-stock (yarn that has been unused for over 6 months). In addition, in the process of implementing measurement systems, several firms discovered huge amounts of yarn they did not even know they had, because of poor records and storage practices. By cataloguing the yarn, reducing old stock by including it in new designs or selling it, introducing restocking norms for future purchases, and monitoring inventory on a daily basis, the firms dramatically reduced their inventories. In fact US automotive firms achieved much greater reductions in inventory levels (as well as quality improvements) when they adopted the Japanese lean manufacturing technology beginning in the 1980s. Many firms reduced inventory levels from several months to a few days by moving to just-in-time production (Womack, Jones and Roos, 1991).

Finally, in column (4) we look at the intention to treat (ITT), which is the average reduction in the yarn inventory after the intervention in the treatment plants versus the control plants. We see the intervention is associated with an average reduction in yarn inventory of (exp(-.189)-1=) 17.1%.

IV-C Efficiency

In Table 6 we look at the impact of management practices on the efficiency of firms operations. Efficiency here is measured as the percentage of time the looms were operating, with 100% representing full efficiency. This is a basic measure of factory productivity, and was used for example as the output measure in the Ichiniowski, Prennushi and Shaw (1997) paper on steel mills.

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[23] We do not show figures for Inventory or Efficiency as these are seasonal (unlike the quality-defects index). As a result because the treatment and control firms have different start dates, so they can not be appropriate compared without time dummies.

The results are presented for the 18 plants for which we have efficiency data. In column (1) we present the fixed-effects OLS results which regresses the monthly efficiency numbers on the plant level management practices, plant fixed effects, and a set of monthly time dummies. The standard errors are clustered at the firm level to allow for any potential correlation across different experimental plants within the same firm. We see that increasing the adoption of management practices by 10 percentage points would be associated with a 0.938% increase in efficiency. In Table 6, column (2), we see the impact of management instrumented with the intervention displays a similar point estimate of 11.291, again somewhat higher than the OLS estimates. In column (3) we run the robustness test with only wave 2 treatment and control firms, once again finding similar results as the full sample IV estimation.

Finally, in column (3) we look at the intention to treat (ITT) and see a point estimate of 2.633. This is insignificant, in part because the efficiency gains take several months to arise so that with only six months of post-treatment data the average post-treatment level of efficiency is not significantly higher than the pre-treatment level. We expect that this is likely to change as we continue to collect data through to April 2010.

There are several reasons for these increases in efficiency. First, undertaking routine maintenance of the looms, especially following the manufacturers' instructions, reduces breakdowns. Second, collecting and monitoring the breakdown data also helps highlight looms, shifts, designs and yarn-types associated with more breakdowns and facilitates pro-actively addressing these. Third, visual displays around the factory floor together with the incentives schemes against these performance metrics motivate workers to improve operating efficiency. Since these incentives are partly individual based and partly group based, workers are motivated both by personal and group rewards to keep their efficiency levels high. Fourth, advance loom planning helps to reduce the amount of time weaving machine lie idle waiting for warp beams (weaving looms need warp beams from the warping looms). Previously looms would frequently lie idle waiting for beams, but advanced planning of warp beam delivery two weeks ahead means plants can exchange warp beams (even between different firms) to keep looms running at full capacity. Finally, keeping the factory floor clean and tidy reduces the number of accidents, for example reducing incidents like tools falling into machines or fires damaging equipment. Again the experience from Lean manufacturing is the collective impact of these procedures can lead to extremely large improvements in operating efficiency.

In table 7 we also estimate the plant level heterogeneity of the estimated impact of the management practices. To do this we run our preferred fixed-effects IV estimation on each treatment plant individually and all the control plants. This gives us some idea of the variation in the impact across the different plants. As can be seen from columns (1) and (2) for quality and inventories the estimated variation is wide, but even for the 10% percentile the point-estimates suggest an improving effect of management (quality is improving and inventory falling). In column (3) we see that at the 10% percentile for efficiency the estimated impact negative, suggesting some potentially greater heterogeneity in the impact on efficiency across the plants. Possibly this reflects the longer time delays between the changes in management and the improvements in efficiency, leading to a greater variation in estimated short-run impact.

IV-D Are the improvements in performance due to Hawthorne effects?

Hawthorne effects are named after the experiments carried out by industrial engineers in the Hawthorne Works in the 1920s and 1930s which attempted to raise productivity. The results apparently showed that simply running experiments led to an improvement in performance, with the most cited result being that both reducing and increasing light levels led to higher productivity. While these putative Hawthorne effects in the original experiments have long been disputed (e.g. Levitt and List, 2009), there is a serious potential concern that some form of the Hawthorne effect is causing our observed increase in plant performance.

However, we think this is unlikely for a series of reasons. First, our control plants also had the consultants on site over a similar period of time as the treatment firms. Both sets of plants got the initial diagnostic period and the follow-up measurement period, with the only difference being the treatment plants also got an intensive intermediate 4 month implementation stage. Hence, it cannot be simply the presence of the consultants or the measurement of performance generating the improvement in performance. Second, the improvements in performance take time to arise, and arose in quality, inventory and efficiency where the majority of the management changes took place (see Table 2). Third, these improvements persisted for many months after the intervention period, so are not some temporary phenomena due to increased attention. Finally, the firms themselves also believed these improvements arose from better management practices, which was the motivation for them spreading these practices out to their other plants not involved in the experiments.

V WHY ARE MANY INDIAN FIRMS BADLY MANAGED?

V.A. The estimated impact of management practices on profits and productivity

In Table 8 we provide some estimates of the magnitudes of the profitability and productivity impact of the interventions, with more details in Appendix A. Firms did not provide us with any profit and loss accounts, so we have estimated the impact on profitability from the quality, inventory and efficiency improvements.[24] Our methodology here is very simple: for example, if a given improvement in practices is estimated to reduce inventory stock by X tons of yarn, we map this into profits using conservative estimates of the cost of carrying X tons of yarn. Or if it reduces the numbers of hours required to mend defects we estimated this reduction in hours on the firms total wage bill. These estimates are medium-run because, for example, it will take a few months for the firms to reduce their mending manpower.

<u>Profits:</u>

The top panel of Table 8 focuses on profits. In the first row we see that the improvements in management practices should have increased profits via reducing mending costs by about \$27,265 for the intervention. The reason is the reduction in quality defects should lead to a fall in the mending manpower, which has an annual average wage bill of \$41,000. Mending is

[24] We could obtain the public profit and loss accounts, but it was unclear how accurate these were. We did not ask firms for their private profit and loss accounts (if they even kept them) as they would have been likely to refuse given the fears over them leaking out to the Indian tax authorities.

generally piece-work so that lower levels of defects lead directly to a lower mending wage bill. In the second row we see the reduction in defects also increased the level of fabric output by $248,713 by reducing the amount of fabric waste. Repairing defects leads to about a 5% loss of fabric sales because many defects cannot be repaired and have to be cut out, or are sold at large reductions.[25] Reducing the number of defects should lead directly to a reduction in the amount of wasted fabric, and thus an increase in output. In the third row we calculate that the reduction in inventory levels from the intervention reduced annual costs by about $13,360. This was because yarn costs about 22% a year to hold given the 15% nominal interest rates on bank loans, the 3% storage costs and 4% depreciation costs. In the fourth row we see the intervention and full-adoption increases in efficiency are estimated to increase profits by $184,760 because of the higher sales from the additional output. The total increase in profits was estimated to be around $474,000, which is about an increase in profits of about 24%.[26]

These increases in profits are lower bounds in three senses. First, they take the firms' choice of capital, labor and product range as given. But in the long-run the firms can re-optimize. For example, with fewer machine breakdowns each weaver can manage more machines, so the number of weavers can be decreased. Second, many of the management practices are arguably complementary, so they are much more effective when introduced jointly (e.g. Milgrom and Roberts, 1990). However, the intervention time-horizon was too short to change many of the complementary human-resource practices, so the full rewards would not be realized. For example, providing employees with rewards for performance above their baseline requires defining the baseline – such as the average level of efficiency over the preceding year – but this is itself impacted by the operational management interventions. As a result many firms did not want to introduce the performance bonuses until after the other interventions had stabilized and they could calculate the appropriate baseline. As a result the full impact of the interventions will take time to accrue. Third, the intervention was narrow in focus in that other management practices around activities like finance, strategy, marketing and procurement were not been addressed.

To evaluate the net increase in profit for these improvements in management practices we also need to calculate the costs of these changes (ignoring for now any costs of consulting). These costs were extremely small, averaging less than $2000 per firm.[27] So in the absence of any costs of consulting to introduce these new management practices – which would have been substantial if firms had paid themselves – it would clearly be highly profitable to do so.

Productivity:

The bottom panel of Table 7 estimates the impact of the intervention on productivity. This is based on an assumed constant-returns-to-scale Cobb-Douglas production function:

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[25] For example, one of the most common quality defects was color streaking in the fabric from different shades of yarn having been accidently used in the same piece of fabric. This fabric is unusable for most clothing so is typically sold at a 50% discount as lining material. Another common defect was dirt and grease stains, which are often impossible to remove in light-colored fabric.

[26] While we can not obtain the true profit and loss accounts for these firms, we do know the average nominal return on capital within the textile industry (about 15%) and their capital stock ($13.3m on average), yielding annual profits of around $2m.

[27] The $35 of extra labor to help organize the stock rooms and clear the factory floor, about $200 on plastic display boards, about $200 for extra racking for stores rooms, and about $1000 on rewards.

$$Y=AL^{\alpha}K^{1-\alpha} \qquad (1)$$

where Y is value-added (output – materials and energy costs), L is hours of work and K is the net capital stock. Under perfect competition the coefficient α is equal to the labor share of value-added, which is 0.59 in textiles in the 2003-04 Indian Annual Survey of Industries.

The first row in the bottom panel estimates the impact of quality improvements on the reduction in repair manpower. Repairing defects is done on a piece by piece basis, so that a reduction in the number of defects implies an equivalent reduction in the number of repair hours. Since repair hours represents 18.7% of all hours across the factory, the 66.5% reduction in QDI estimated from the intervention and full-adoption changes in management practices led to an estimated 7.2% increase in productivity. The second row in the bottom panel of Table 7 estimates the productivity impact of the lower waste of fabric in the quality repair process, with an estimated 3.3% for the intervention. The third row of the bottom panel estimates the impact of a lower capital stock from the lower inventory levels, which leads to a 0.9% estimated increase in productivity.

Finally, the fourth row in the bottom panel estimates of the impact of increased production efficiency on total factor productivity. Since efficiency represents the percentage of time the machines are running, any increase in this translates directly into an increase in output, and given the labor and capital inputs are fixed, into an equivalent increase in productivity.[28] Hence, the 4.0% increase in efficiency from the intervention translates directly into proportional increases in productivity.

Overall these productivity numbers are quite substantial – a 15.4% increase from the intervention. And as discussed above we think these are lower bound figures, substantially below the long-run impact of firms improving their management practices. Hence, these numbers suggests that bad management does play an important role in explaining the productivity gap between India and the US.

V.B. Why are firms badly managed?

Given the evidence in section (V.A) above on the large increase in profitability from the introduction of these modern management practices, the obvious question is: why had firms not already adopted these before? To investigate this we asked our consultants to document every other month the reason for any non-adoption of the 38 practices in each plant. To do this consistently we developed a flow-chart (see Figure 4) which runs through a series of questions to understand the root cause for the non-adoption of each individual practice. They collected this data from extensive discussions with owners, managers and workers, plus their observations from working daily in the plants.

As an example of how this flow chart works, imagine a plant that does not record quality defects (the first practice in quality control in Table 2). The consultant would first ask if there

[28] In fact with higher efficiency lower labor is needed because if machines breakdown less frequently workers can supervise more machines, so that in the long-run these figures would be an underestimate of the impact.

was some external constraint, like labor regulations, preventing this, which we found never to be the case.[29] They would then ask if the plant was aware of this practice, which in the example of quality recording systems typically was the case as it's a well known practice. The consultants would then check if the plant could adopt the practice with the current staff and equipment, which again for quality recording systems was always true as it is a simple process. Then they would ask if the owner believed it would be profitable to record quality defects, which was often the constraint on adopting this practice. The owner often argued their quality was so good they did not need to record quality defects. This view was mistaken because while these plants' quality might have been good compared to other low-quality Indian textile plants, by international standards their quality was very poor. So, as shown in Figure 3, when they did adopt basic quality control practices they substantially improved their production quality. So, in this case the reason for non-adoption would be "incorrect information" as the CEO had incorrect information on the cost-benefit calculation for quality control processes.

The overall results for non-adoption of management practices are tabulated in Table 9, for the treatment plants, control plants and the non-experimental plants (the plants in the same firm as the treatment plants). This is tabulated at 2 monthly intervals starting the month before the intervention phase. The rows report the different reasons for non-adoption as a percentage of all practices. So that, for example, the top-left cell (value 38.6) states that in the treatment plants in the month before the intervention 38.6% of practices were not adopted because the plant was unaware of the existence of these practices (they lacked information on these). Looking across the table several results are apparent

First, a major initial barrier to the adoption of these modern management practices is a lack of information about their existence. About 30% of practices were not adopted because the firms were simply not aware of them. These practices tended to be the more advanced practices of regular quality, efficiency and inventory review meetings, posting standard-operating procedures and visual aids around the factory, the use of historical efficiency data for design pricing and scientific inventory methods. Many of these are derived from the Japanese inspired lean manufacturing revolution, and are common across Europe, Japan and the US but apparently have yet to permeate Indian manufacturing.

Second, another major initial barrier was incorrect information, in that firms may have heard of these practices but thought they did not apply profitably to them. For example, many of the firms were aware of preventive maintenance but few of them thought it was worth doing this. They preferred to keep their machines in operation until they broke down, and then repair them. But another lesson from the Lean manufacturing revolution is that preventive maintenance reduces long-run downtimes (as faults are typically easier to fix in advance) and also production variability. Production variability itself reduce productivity as it causes other problems along the supply chain – for example, unanticipated breakdowns increase the complexity of production scheduling, increasing the downtimes from mismatched resources.

[29] This does not mean labor regulations do not matter for some practices – for example firing underperforming employees – but they did not directly impinge adopt the immediate adoption of the 38 practices in Table 2.

Third, as the intervention progressed the lack of information constraint was rapidly addressed. It was easy for the consultants to inform the firms about modern management practices. However, the incorrect information constraints were harder to address. This was because the owners had their prior beliefs about the efficacy of a practice and it took time to change these. This was often done using pilot changes on a few machines in the plant or with evidence from other plants in the experiment. For example, the consultants often started by persuading the managers to undertake preventive maintenance on a set of trail machines, and once it was proven successful it was rolled out to the rest of the factory. And as the consultants demonstrated the positive impact of some of these initial practice changes, the owners increasingly trusted them and would adopt more of the more complex recommendations, like introducing performance incentives for managers.[30]

Fourth, once the informational constraints were addressed other constraints arose. For example, even if the owners became convinced of the need to adopt a practice they would often take several months to execute these. This was particularly pertinent in the non-experimental plants where the consultants were not on-site to drive the changes. This matches up to the evidence on procrastination in other contexts, for example Kenyan farmers investing in fertilizer (Duflo, Kremer and Robinson, 2009) or farmers in Ghana adopting new technologies (Conley and Udry, 2010).

Fifth, manager incentives were also a cause of non-adoption of a few percent of these practices. In these firms mid-level managers did not receive any incentive pay, and they had very limited promotion incentives since the directors of all mid-size textiles firms were family members. Hence, their incentives to perform beyond the levels required to keep their jobs was muted. As a result many of the managers were happy to adopt management practices that were standard in the industry, but reluctant to do anything further if this involved additional effort. This highlights how the adoption of management practices is cross-linked, with poor human-resource management practices impeding the adoption of other management practices.

Finally, somewhat surprisingly we did not find evidence for the direct impact of a set of other factors highlighted in the literature on capital investment. One such factor is capital constraints, which are a significant obstacle to the expansion of micro-enterprises (e.g. De Mel, McKenzie and Woodruff, 2008). Our evidence suggested that the medium to large firms involved in our experiment were not cash-constrained. We collected data on all the investments for our 17 firms over the period April 2008 until April 2010 and found the firms invested a mean (median) of $880,000 ($140,000). For example, several of the firms were setting up new factories or adding machines, apparently often financed by bank loans. Certainly, this scale of investment suggests that investment on the scale of $2000 (the first-year costs of these management changes, ignoring the consultants' fees) to improve the factories' management practices is unlikely to be directly impeded by financial constraints.

[30] These sticky priors highlight one reason why management practices appear to take several years to change in the US and Europe. The evidence on this is anecdotal, but for example, the private equity industry has a 3 year minimum for a management turn around. Similarly, consulting firms typically take at least 18 months to execute large change management programs.

Of course financial constraints could impede hiring in international consultants. The market cost of our free consulting would be at least $500,000, and as an intangible investment it would be difficult to collateralize.[31] Hence, while financial constraints do not appear to directly block the implantation of better management practices, they may hinder firms' ability to improve their current management practices using external consultants. On the other hand, our estimates of the incremental profitability from adopting modern management practices suggest cost recovery in as little as one year.

Another factor we that played a limited direct role was poor infrastructure. For example, unreliable electricity provision is a major impediment to productivity in developing countries (e.g. World Bank, 2004). We certainly saw evidence of this in that, for example, Tarapur and Umbergaon had weekly electricity blackouts which lowered production levels on the blackout days (most firms had generators that could cover only about 50% of their electricity needs). However, this did not appear to explain firms' bad management, since they successfully adopted many of the 38 key textile practices during the intervention period, over the course of which the infrastructure was not improved. This reflects that fact these practices change the way firms internally operate and are relatively independent from infrastructure or external problems.

The same reasoning also applies to corruption, since again there is no evidence the levels of potential corruption changed over the intervention period. Also, looking at the list of individual practices it is hard to identify many that would be constrained by corruption.

V.C. How do badly managed firms survive?

We have shown that management matters, with improvements in management practices improving plant-level outcomes. One response from economists might then be to argue that poor management can at most be a short-run problem, since in the long run better managed firms should take over the market. Yet many of our firms have been in business for 20 years and more.

One reason why better run firms do not dominate the market is constraints on growth through managerial span of control. In every firm in our sample, only members of the owning family are company directors – that is in managerial positions with major decision-making power over finances, purchases, operations or employment. paper. Non-family members are given junior managerial positions that have power only over low-level, day-to-day activities. The reason is the family members do not trust the non-family members not to steal from the firm. For example, they are concerned if they let their plant managers run procurement they might buy yarn at inflated rates from friends and receive kick-backs.

[31] Our international consulting firm estimated that to offer a standard consulting team to these firms at market rates would cost at least $500,000. This is much more expensive than our costs per firm because: (I) we achieved substantial scale economies from working with a large number of firms simultaneously; and (II) we had 50% rates on the consultants and no partner charges.

A key reason for this inability to decentralize is the poor rule of law in India. Even if directors found managers stealing their ability to successfully prosecute them and recover the assets is minimal because of the inefficiency of Indian courts. In contrast, in the US if a manager was found stealing from a firm it is likely they could be successfully prosecuted and much of the assets recovered. A compounding reason for the inability to decentralize in Indian firms is bad management, as this means they cannot keep good track of materials and finance, so may not even able to identify theft within their firms. [32]

As a result of this inability to decentralize every factory in the firm requires a family member on-site to manage it. This means firms can only expand if male family members are available to take up plant manager positions. Thus, an important correlate of firm size in our firms was the number of male family members of the owners. For example, the number of brothers and sons of the leading director has a correlation of 0.689 with the total employment size of the firm, compared to 0.223 for their average management score. In fact the best managed firm in our sample – which was also a publicly quoted firm and apparently extremely profitable – had only one (large) production plant, in large part because the owner had no brothers or sons to run additional plants. This matches the ideas of the Lucas (1978) span of control model, that there are diminishing returns to how much additional productivity better management technology can generate from a single manager. In this model the limits to firm growth restrict the ability of highly productive firms to drive out the lower productivity firms from the market. In our India firms this span of control restriction is extremely binding so productive firms do not grow large and drive unproductive firms out from the market. This matches plant-level productivity data from China and India (Hsieh and Klenow, 2009) as well as firm-level organizational survey data (Bloom, Sadun and Van Reenen, 2009).

Entry also appears limited by the difficulty of separating ownership from control. The supply of new firms is limited by the numbers of wealthy families with finance and male family members available to run textiles plants. Given the rapid growth of other industries in India – like software and real-estate – entry into textile manufacturing is limited. Even our firms were often taking cash from their textile businesses to invest in other businesses, like real-estate and retail. And even if an entrant had funding there is no obvious guarantee their management practices would be better than the incumbent firms.

Hence, the equilibrium appears to be that Indian wage rates are extremely low so that firms can survive while operating with poor management practices. Because spans of control are constrained productive incumbent firms are limited from expanding and so do not drive out the badly run firms. And because entry is limited new firms do not enter rapidly. As a result the situation approximates a Melitz (2003) style model where firms have very high decreasing returns to scale, entry rates are low, and initial productivity draws are low (because good

[32] Another compounding factor is these firms had poor human resources management practices. None of the firms had a formalized development or training plan for their managers, and managers could not be promoted because only family members could become directors. As a result managers lacked career motivation within the firm. In contrast in the Indian software and finance industries firms place a huge emphasis on development and training to motivate employees and build trust, which is essential for delegation in the absence of a strong level system (see also Banerjee and Duflo (2000)).

management practices are not widespread). The resultant equilibrium has a low average level of productivity, a low wage level, a low average firm-size, and a large dispersion of firm-level productivities.

VI CONCLUSIONS

Management does matter. We have implemented a randomized experiment which gave managerial consulting services to textile plants in India. This experiment led to improvements in basic management practices, with plants adopting lean manufacturing techniques which have been standard for decades in the developed world. These improvements in management practice led to plants improving the quality of their production, reducing excess inventory levels, and improving efficiency. The result was an improvement in profitability and productivity.

What are the implications of this for public policy? First, our results suggest that firms were not implementing the better practices on their own because of lack of information and knowledge, and that to really improve quality firms needed detailed instruction in how to implement better practices. This suggests a need for better knowledge and training programs in India, and in developing countries more generally. This would include high quality business school education to teach managers better management practices, and a more vibrant local consulting industry with the ability to signal quality through reputation building. While both these are private sector activities, they depend on the government for a regulatory environment which makes entry easy and which allows quality to be the main determinant of success. A second method for knowledge transference comes from the presence of multinationals. Indeed, many of the consultants working for the international consulting firm hired by our project had worked for multinationals in India, learning from their state-of-the-art manufacturing management processes. Yet a variety of legal, institutional, and infrastructure barriers have limited the extent of multinational expansion within India, limiting the spread of knowledge on better manufacturing among the Indian managerial labor force. Finally, our results also suggest that a weak legal environment has limited the scope for well-managed firms to grow. So that improving the legal environment should encourage productivity enhancing reallocation, helping to drive out badly managed firms.

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APPENDIX

A1. Estimations of profitability and productivity impacts.

We first generate the estimated impacts on quality, inventory and efficiency. To do this we take the 0.352 change in management practices in the treatment firms (see Table 2) and multiply this by the coefficients from the full sample column for IV regressions. For quality this generates a predicted reduction in defects of 66.5% (0.352*1.889), for inventory a predicted reduction of 26.4% (0.352*0.749) and for efficiency a predicted increase of 4.0% (0.352*11.29).

Mending wage bill:

Estimated by recording the total mending hours, which is 71,700 per year on average, times the mending wage bill which is 36 rupees (about $0.72) per hour. Since mending is undertaken on a piece-wise basis – so defects are repaired individually – a reduction the severity weighted defects should lead to a proportionate reduction in required mending hours.

Fabric revenue loss from non grade-A fabric:

Waste fabric estimated at 5% in the baseline, arising from cutting our defect areas and destroying and/or selling at a discount fabric with unfixable defects. Assume increase in quality leads to a proportionate reduction in waste fabric.

Inventory carrying costs:

Total carrying costs of 22% calculated as interest charges of 15% (average prime lending rate of 12% over 2008-2010 plus 3% as firm-size lending premium – see for example http://www.sme.icicibank.com/Business_WCF.aspx?pid), 3% storage costs (rent, electricity, manpower and insurance) and 4% costs for physical depreciation and obsolescence (yarn rots over time and fashions change).

Increased output from higher efficiency

The machines operated at an average efficiency rate of 73.4% prior to the interventions. This meant that 26.6% of the time a random machine would not be producing yarn. Raising the efficiency level leads directly to more output as the number of machines is fixed. This is achieved by reducing machine breakdowns and speeding up beam-gaiting (the process of changing warp beams on the yarn).

Labor and capital factor shares:

Labor factor share of 0.58 calculated as total labor costs over total value added using the “wearing apparel” industry in the most recent (2004-05) year of the Indian Annual Survey of industry. Capital factor share defined as 1-labor factor share, based on an assumed constant returns to scale production function and perfectly competitive output markets.

Table 1: The field experiment sample

	All				Treatment	Control	Diff
	Mean	Median	Min	Max	Mean	Mean	p-value
Sample sizes:							
Number of plants	28	n/a	n/a	n/a	19	9	n/a
Number of experimental plants	20	n/a	n/a	n/a	14	6	n/a
Number of firms	17	n/a	n/a	n/a	11	6	n/a
Plants per firm	1.65	2	1	4	1.73	1.5	0.393
Firm/plant sizes:							
Employees per firm	273	250	70	500	291	236	0.454
Employees, experimental plants	134	132	60	250	144	114	0.161
Hierarchical levels	4.4	4	3	7	4.4	4.4	0.935
Annual sales $m per firm	7.45	6	1.4	15.6	7.06	8.37	0.598
Current assets $m per firm	13.3	7.9	3.02	30.8	13.3	12.0	0.837
Daily mtrs, experimental plants	5560	5130	2260	13000	5,757	5,091	0.602
Management and plant ages:							
BVR Management score	2.60	2.61	1.89	3.28	2.50	2.75	0.203
Management adoption rates	0.274	0.260	0.08	0.553	0.255	0.328	0.248
Age, experimental plant (years)	19.4	16.5	2	46	20.5	16.8	0.662
Performance measures							
Quality defects index	4.88	2.32	0.65	19.96	3.20	7.93	0.333
Raw materials inventory (kg)	59,497	61,198	6,721	149,513	59,222	60,002	0.957
Operating efficiency (%)	70.77	72.8	26.2	90.4	70.2	71.99	0.758

Notes: Data provided at the plant and/or firm level depending on availability. **Number of plants** is the total number of textile plants per firm including the non-experimental plants. **Number of experimental plants** is the total number of treatment and control plants. **Number of firms** is the number of treatment and control firms. **Plants per firm** reports the total number of other textiles plants per firm. Several of these firms have other businesses – for example retail units and real-estate arms – which are not included in any of the figures here. **Employees per firm** reports the number of employees across all the textile production plants, the corporate headquarters and sales office. **Employees per experiment plant** reports the number of employees in the experiment plants. **Hierarchical levels** displays the number of reporting levels in the experimental plants – for example a firm with workers reporting to foreman, foreman to operations manager, operations manager to the general manager and general manager to the managing director would have 4 hierarchical levels. **BVR Management score** is the Bloom and Van Reenen (2007) management score for the experiment plants. **Management adoption rates** are the adoption rates of the management practices listed in Table 2 in the experimental plants. **Annual sales ($m)** and **Current assets ($m)** are both in 2009 US $million values, exchanged at 50 rupees = 1 US Dollar. **Daily mtrs, experimental plants** reports the daily meters of fabric woven in the experiment plants. Note that about 3.5 meters is required for a full suit with jacket and trousers, so the mean plant produces enough for about 1600 suits daily. **Age of experimental plant (years)** reports the age of the plant for the experimental plants. Note that none of the differences between the means of the treatment and control plants are significant. **Quality defects index** is a weighted average score of quality defects per intervention. **Raw materials inventory** is the stock of yarn per intervention. **Operating efficiency** is the percentage of the time the machines are producing fabric per intervention.

Table 2: The textile management practices adoption rates

Area	Specific practice	Pre-intervention *level* of adoption		Post-intervention *change* in adoption	
		Treatment	Control	Treatment	Control
Factory Operations	Preventive maintenance is carried out for the machines	0.429	0.667	0.214	0
	Preventive maintenance is carried out per manufacturer's recommendations	0.071	0	0.142	0.167
	The shop floor is marked clearly for where each machine should be	0.071	0.333	0.142	0
	The shop floor is clear of waste and obstacles	0	0.167	0.142	0
	Machine downtime is recorded	0.571	0.667	0.357	0.167
	Machine downtime reasons are monitored daily	0.429	0.167	0.5	0.167
	Machine downtime analyzed at least fortnightly & action plans implemented to try to reduce this	0	0.167	0.571	0
	Daily meetings take place that discuss efficiency with the production team	0	0.167	0.857	0.500
	Written procedures for warping, drawing, weaving & beam gaiting are displayed	0.071	0.167	0.500	0
	Visual aids display daily efficiency loomwise and weaverwise	0.214	0.167	0.571	0.167
	These visual aids are updated on a daily basis	0.143	0	0.643	0.167
	Spares stored in a systematic basis (labeling and demarked locations)	0.143	0.333	0.143	0
	Spares purchases and consumption are recorded and monitored	0.571	0833	0	0
	Scientific methods are used to define inventory norms for spares	0	0.167	0	0
Quality Control	Quality defects are recorded	0.929	1	0.071	0
	Quality defects are recorded defect wise	0.286	0.167	0.714	0.833
	Quality defects are monitored on a daily basis	0.286	0.333	0.714	0.333
	There is an analysis and action plan based on defects data	0	0.167	0.714	0
	There is a fabric gradation system	0.571	0.833	0.357	0
	The gradation system is well defined	0.500	0.667	0.429	0
	Daily meetings take place that discuss defects and gradation	0.071	0.167	0.786	0
	Standard operating procedures are displayed for quality supervisors & checkers	0	0	0.643	0
Inventory Control	Yarn transactions (receipt, issues, returns) are recorded daily	0.928	1	0.071	0
	The closing stock is monitored at least weekly	0.214	0.167	0.571	0.333
	Scientific methods are used to define inventory norms for yarn	0	0	0.167	0
	There is a process for monitoring the aging of yarn stock	0.231	0	0.538	0
	There is a system for using and disposing of old stock	0	.2	0.692	0.600
	There is location wise entry maintained for yarn storage	0.357	0.167	0.143	0
Loom Planning	Advance loom planning is undertaken	0.429	0.833	0.143	0
	There is a regular meeting between sales and operational management	0.429	0.500	0.214	0.167
Human Resources	There is a reward system for non-managerial staff based on performance	0.571	0.667	0.071	0
	There is a reward system for managerial staff based on performance	0.214	0.167	0.214	0

	There is a reward system for non-managerial staff based on attendance	0.214	0.333	0.214	0
	Top performers among factory staff are publicly identified each month	0.071	0	0.143	0
	Roles & responsibilities are displayed for managers and supervisors	0	0	0.500	0
Sales and Orders	Customers are segmented for order prioritization	0	0	0	0
	Orderwise production planning is undertaken	0.692	1	0.231	0
	Historical efficiency data is analyzed for business decisions regarding designs	0	0	0.143	0
All	Average of all practices	0.255	0.328	0.352	0.093
p-value for the difference between the average of all practices		0.248		0.000	

Notes: Reports the 38 individual management practices measured before, during and after the management intervention. The columns **Pre Intervention *level* of Adoption** report the pre-intervention share of plants adopting this practice for the 14 treatment and 6 control plants. The columns **Post Intervention *increase* in Adoption** report the changes in adoption rates between the pre-intervention period and 4 months after the end of the diagnostic phase (so right after the end of the implementation phase for the treatment plants) for the treatment and control plants. The **p-value for the difference between the average of all practices** reports the significance of the difference in the average level of adoption and the increase in adoption between the treatment and control groups.

Table 3: The impact of the treatment on management practice scores

Management practices	All (1)	All (1)	Ops (3)	Quality (4)	Invent (5)	Loom plan (6)	HR (6)	Sales (6)
Panel A:								
Intervention	0.296	0.214	0.208	0.313	0.197	0.130	0.190	0.083
	(0.019)	(0.024)	(0.042)	(0.046)	(0.062)	(0.053)	(0.062)	(0.037)
R-squared	0.790	0.881	0.854	0.817	0.805	0.888	0.847	0.639
Panel B:								
Cumulative intervention	0.017	0.013	0.012	0.019	0.012	0.007	0.013	0.005
	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)	(0.004)	(0.002)
Cumulative intervention squared[a]	-0.010	-0.006	-0.015	-0.025	-0.017	-0.008	-0.015	-0.005
	(0.002)	(0.000)	(0.002)	(0.005)	(0.004)	(0.005)	(0.005)	(0.004)
R-squared	0.871	0.903	0.868	0.843	0.822	0.891	0.874	0.653
Time FEs (104)	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Plant FEs (20)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Plants	20	20	20	20	20	20	20	20
Firm clusters	17	17	17	17	17	17	17	17
Observations	2184	2184	2184	2184	2184	2184	2184	2184

Notes: All regressions use the monthly data for the months in which management scores were collected/imputed. All columns include a full set of 20 plant dummies and from column (2) onwards includes a full set of 9 calendar monthly time dummies. Standard errors boostrap clustered at the firm level. **All** is the overall adoption rate of the 38 management practices. **Ops** is the average adoption rate of the 14 factory operations practices. **Quality** is the average adoption rate of the 8 quality control practices. **Invent** is the adoption rate of the 6 inventory control practices. **Loom plan** is the adoption rate of the 2 loom planning practices. **HR** is the average adoption rate of the 5 human resources practices. **Sales** is the average adoption rate of the 3 sales and orders practices. **Cumulative intervention** is a cumulative count of the months since the start of the implementation in each plant (treatment plants only), and value zero before. **Cumulative intervention squared** is the square of the count of the months since the start of the implementation dated from the diagnostic phase, and value zero before. **Time FEs** report the inclusion of a full set of calendar month time fixed effects. **Plant FEs** report the inclusion of a full set of plant-level fixed effects. **Plants** reports the number of plants in the regression (data is not available for every indicator for every plant). **Firm clusters** reports the number of firm level clusters in the regression.

[a] Denotes coefficient and standard error multiplied by 100 for scaling purposes

Table 4: The impact of management on quality (measured by number of defects)

Dependent Var. is log (Quality Defects Index)	FE-OLS (1)	FE-IV (2)	FE-IV (3)	ITT (4)
Sample	All	All	Wave 2 + Control	All
Management	-0.997	-1.889	-2.756	
	(0.435)	(0.693)	(1.324)	
Intervention (implementation)				-0.417
				(0.185)
Instruments		cumulative intervention, cumulative intervention^2	cumulative intervention, cumulative intervention^2	
Week FEs (97)	Yes	Yes	Yes	Yes
Plant FEs (18)	Yes	Yes	Yes	Yes
Plants	18	18	14	18
Firm clusters	16	16	13	16
Observations	1251	1251	922	1251

Notes: All regressions use a full set of plant and calendar week dummies. Standard errors bootstrap clustered at the firm level. The third column uses just the wave 2 treatment plus control firms, whose diagnostic phases started within 2 months of each other so have the most similar timing. **Quality Defects Index** is a weighted average score of quality defects, so higher numbers imply worse quality products (more quality defects). **Management** is the adoption of the 38 management practices listed in table 2. **Intervention (implementation)** is a plant level indicator taking a value of 1 after the implementation phase has started at a treatment plant. **Cumulative intervention** is a cumulative count of the months since the start of the implementation in each plant (treatment plants only), and value zero before. **Cumulative intervention^2** is the square of the count of the months since the start of the intervention dated from the implementation phase, and value zero before. **FE-OLS** reports results with plant estimations. **FE-IV** reports the results where the management variable has been instrumented with the cumulative intervention time and cumulative intervention squared. **ITT** reports the intention to treat results from regressing the dependent variable directly on the 1/0 intervention indicator. **Time FEs** report the inclusion of a full set of calendar week time fixed effects. **Plant FEs** report the inclusion of a full set of plant-level fixed effects. **Plants** reports the number of plants in the regression (data is not available for every indicator for every plant). **Firm clusters** reports the number of firm level clusters in the regression.

Table 5: The impact of textile management practices on inventory

Dependent Variable is Log (inventory)	FE-OLS	FE-IV	FE-IV	ITT
	(1)	(2)	(3)	(4)
Sample	All	All	Wave 2 + Control	All
Management	-0.661	-0.749	-0.807	
	(0.241)	(0.339)	(0.499)	
Intervention (implementation)				-0.187
				(0.092)
Instruments		cumulative intervention, cumulative intervention^2	cumulative intervention, cumulative intervention^2	
Week FEs (96)	Yes	Yes	Yes	Yes
Plant FEs (18)	Yes	Yes	Yes	Yes
Plants	16	16	12	16
Firm clusters	14	14	11	14
Observations	1411	1411	922	1411

Notes: All regressions use a full set of plant and calendar week dummies. Standard errors bootstrap clustered at the firm level. The third column uses just the wave 2 treatment plus control firms, whose diagnostic phases started within 2 months of each other so have the most similar timing. **Management** is the adoption of the 38 management practices listed in table 2. **Intervention (implementation)** is a plant level indicator taking a value of 1 after the implementation phase has started at a treatment plant. **Cumulative intervention** is a cumulative count of the months since the start of the implementation in each plant (treatment plants only), and value zero before. **Cumulative intervention^2** is the square of the count of the months since the start of the intervention dated from the implementation phase, and value zero before. **FE** reports results with plant and time dummies. **FE-IV** reports the results where the management variable has been instrumented with the cumulative intervention time and cumulative intervention squared. **ITT** reports the intention to treat results from regressing the dependent variable directly on the 1/0 intervention indicator. **Time FEs** report the inclusion of a full set of calendar week time fixed effects. **Plant FEs** report the inclusion of a full set of plant-level fixed effects. **Plants** reports the number of plants in the regression (data is not available for every indicator for every plant). **Firm clusters** reports the number of firm level clusters in the regression.

Table 6: The impact of textile management practices on machine efficiency

Dependent Variable is Efficiency	FE-OLS (1)	FE-IV (2)	FE-IV (3)	ITT (4)
Sample	All	All	Wave 2 + Control	All
Management	9.380	11.291	13.423	
	(4.105)	(5.078)	(6.576)	
Intervention (implementation)				2.633
				(1.643)
Instruments		cumulative intervention, cumulative intervention^2	cumulative intervention, cumulative intervention^2	
Week FEs (96)	Yes	Yes	Yes	Yes
Plant FEs (18)	Yes	Yes	Yes	Yes
Plants	19	19	17	19
Firm clusters	15	15	14	15
Observations	1730	1730	1538	1730

Notes: All regressions use a full set of plant and calendar week dummies. Standard errors bootstrap clustered at the firm level. The third column uses just the wave 2 treatment plus control firms, whose diagnostic phases started within 2 months of each other so have the most similar timing. **Management** is the adoption of the 38 management practices listed in table 2. **Intervention (implementation)** is a plant level indicator taking a value of 1 after the implementation phase has started at a treatment plant. **Cumulative intervention** is a cumulative count of the months since the start of the implementation in each plant (treatment plants only), and value zero before. **Cumulative intervention^2** is the square of the count of the months since the start of the intervention dated from the implementation phase, and value zero before. **FE** reports results with plant and time dummies. **FE-IV** reports the results where the management variable has been instrumented with the cumulative intervention time and cumulative intervention squared. **ITT** reports the intention to treat results from regressing the dependent variable directly on the 1/0 intervention indicator. **Time FEs** report the inclusion of a full set of calendar month time fixed effects. **Plant FEs** report the inclusion of a full set of plant-level fixed effects. **Firm clusters** reports the number of firm level clusters in the regression.

Table 7: Heterogeneity of impact of management practices across plants

Dependent Variable:	Quality Defects Index	Inventory	Efficiency
	(1)	(2)	(3)
Pooled sample (from above)	-1.889	-0.749	11.291
Standard deviation of individual treatment plant coefficients	4.781	0.652	12.178
10th percentile plant coefficient	-0.948	-0.184	-2.120
25th percentile plant coefficient	-1.073	-0.186	1.503
50th percentile plant coefficient	-1.931	-0.610	8.923
75th percentile plant coefficient	-3.883	-1.163	21.368
90th percentile plant coefficient	-4.955	-1.521	28.758

Notes: All regressions show the coefficient on the management practice adoption score, with a full set of plant and calendar week dummies. The **pooled sample** takes the coefficients from column (2) in Tables 4 to 6 above. The individual plant coefficients run the IV regressions with the full set of control plants plus the individual treatment plant. This regressions are run once for each treatment plant, once for each dependent variable. This yields a coefficient for each treatment plant for each outcome. The **standard deviation of plant level coefficients** reports the standard deviation of these coefficients across the treatment plants, while the **10th percentile of plant coefficient** reports the 10th percentile coefficient etc.

Table 8: Estimated average impact of improved quality, inventory and efficiency

Change	Impact	Estimation approach	Estimated impact
Profits (annual in $)			
Improvement in quality	Reduction in repair manpower	Reduction in defects (66.5%) times average mending manpower wage bill of $41,000.	$27,265
	Reduction in waste fabric	Reduction in defects times (66.5%) the average yearly waste fabric (5%) times annual average sales of $7.45m.	$248,713
Reduction in inventory	Reduction in inventory carrying costs	Reduction in inventory (26.4%) times carrying cost of 22% times $230,000 average inventory	$13,360
Increased efficiency	Increased sales	Increase in output of 1.305% times 62% margin times $7.45m sales	$184,760
Total			$474,098
Productivity (%)			
Improvement in quality	Reduction in repair manpower	Reduction in defects (66.5%) times share of repair manpower in total manpower (18.7%) times labor share (0.58) in output	7.2%
	Reduction in waste fabric	Reduction in defects (66.5%) times the average yearly waste fabric (5%)	3.3%
Reduction in inventory	Reduction in capital stock	Reduction in inventory (26.4%) times inventory share in capital (8%) times capital factor share (0.42)	0.9%
Increased efficiency	Increased output	Efficiency impact on productivity (4.0%) given labor and capital do not change	4.0%
Total			15.4%

Notes: Estimated impact of the improvements in the management intervention on firms profitability and productivity through quality, inventory and efficiency using the estimates in Tables 4, 5 and 6. Figure calculated for the average firm. See Appendix A for details of calculations for inventory carrying costs, fabric waste, repair manpower and factor shares.

Table 9: Reasons for bad management, as a percentage (%) of all practices, before and after treatment

Non-adoption reason	Firm group	1 month before	1 month after	3 months after	5 months after	7 months after	9 months after
Lack of information (plants not aware of the practice)	Treatment	38.6	12.8	2.2	0.5	0.4	0.3
	Control	32.1	13.7	8.4	8.4	8.4	n/a
	Non-experimental	30.4	13.0	2.1	0.5	0.5	0.3
Incorrect information (plants incorrect on cost-benefit calculation)	Treatment	29.3	33.3	31.9	29.2	28.5	27.5
	Control	27.6	36.1	38.4	37.9	37.9	n/a
	Non-experimental	34.2	33.2	31.3	28.7	24.7	23.2
Low ability or procrastination of owner (the owner is the reason for non adoption)	Treatment	3.8	9.1	7.2	7.5	7	6.7
	Control	5.8	9.5	9.2	8.4	8.4	n/a
	Non-experimental	5.3	23.4	31.8	35.5	33.2	33.7
Limited manager incentives or authority (plant manager is the reason for non-adoption)	Treatment	1.3	2.1	2.4	3.0	3	3.2
	Control	1.6	1.6	1.6	1.6	1.6	n/a
	Non-experimental	2.4	2.6	2.6	2.6	2.6	2.6
Not profitable (the consultants agree non-adoption is correct)	Treatment	0	0.2	0.4	0.5	0.4	0.4
	Control	0	0	0	0	0	n/a
	Non-experimental	0	0	0	0	0.5	0.5
Other (variety of other reasons for non-adoption)	Treatment	0	0.2	0.4	0.2	0.5	0.5
	Control	0	0	0	0	0	n/a
	Non-experimental	0	0	0	0	0	0
Total	Treatment	73	57.7	44.3	40.9	39.8	38.6
	Control	67.1	60.8	57.6	56.3	56.3	n/a
	Non-experimental	72.3	72.1	67.9	67.3	61.6	60.3

Notes: Show the percentages (%) of practices not adopted by reason for non-adoption, in the treatment plants, control plants and non-experimental plants (the non-experimental plants belonging to firms with a treatment plant). Timing is relative to the start of the treatment phase (the end of the diagnostic phase for the control group and the start of the treatment phase for the other plant in their firm for the non-experimental plants). Covers 532 practices in treatment plants (38 practices in 14 plants), 228 practices in the control plants (38 practices in 6 plants) and 190 practices in the non-experimental plants (38 practices in 5 plants). Non adoption was monitored every other month using the tool shown in Figure 4, based on discussions with the firms' directors, managers, workers, plus regular consulting work in the factories. Note that data is only currently available up to 7 months after the end of diagnostic phase in the control firms.

Exhibit 1: Factories are large compounds containing several buildings.

Factory surrounded by extensive grounds

A group of three buildings within a factory compound

Factory offices (left) and goods loading bay (right)

Factory entrance with gates and a guard post

Exhibit 2: These factories operate 24 hours a day for 7 days a week producing fabric from yarn, with 4 main stages of production

(1) Winding the yarn thread onto the warp beam

(2) Drawing the warp beam ready for weaving

(3) Weaving the fabric on the weaving loom

(4) Quality checking and repair

Exhibit 3: Many parts of these factories were dirty and unsafe

Garbage outside the factory

Garbage inside a factory

Flammable garbage in a factory

Chemicals without any covering

Exhibit 4: The factory floors were disorganized

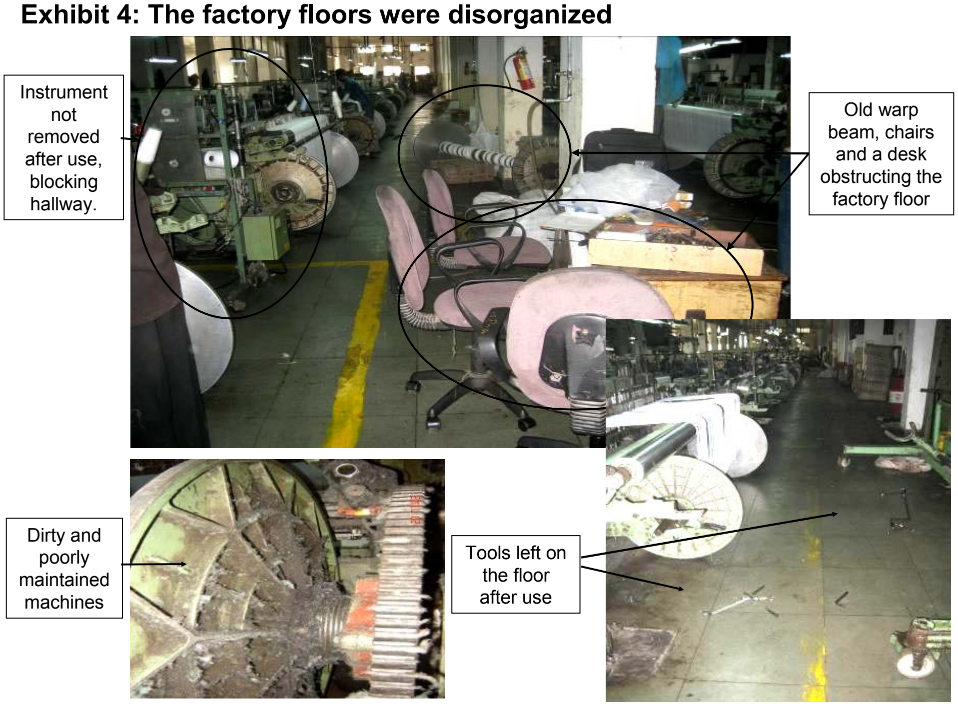


Exhibit 5: The inventory rooms had months of excess yarn, often without any formal storage system or protection from damp

Exhibit 6: The parts stores were also disorganized and dirty

Spares without any labeling or order

No protection to prevent damage and rust

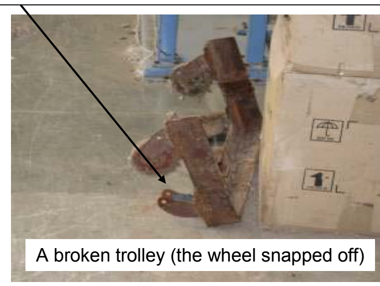
Spares without any labeling or order

Shelves overfilled and disorganized

Exhibit 7: The path for materials flow was often obstructed

Unfinished rough path along which 6 heavy warp beams were taken on wheeled trolleys every day to the elevator, which led down to the looms.

This steep slope, rough surface and sharp angle meant workers often lost control of the trolleys. They crashed into the girder or wall, eventually breaking the trolleys. So now each beam is carried by 6 men.



A broken trolley (the wheel snapped off)

At another factory both warp beam elevators had broken down due to poor maintenance. As a result teams of 7 men carried several warps beams down the stairs every day. This was slow and dangerous.

Exhibit 8: Routine maintenance was usually not carried out, with repairs only undertaken when breakdowns arose, leading to frequent stoppages.

Warp beam being unloaded off a broken loom

Parts being cleaned and replaced on jammed loom

Workers investigating a broken loom

Loom parts being disassembled for diagnosis

Exhibit 9: Quality was so poor that about 20% of manpower was spent on repairing defects at the end of the production process

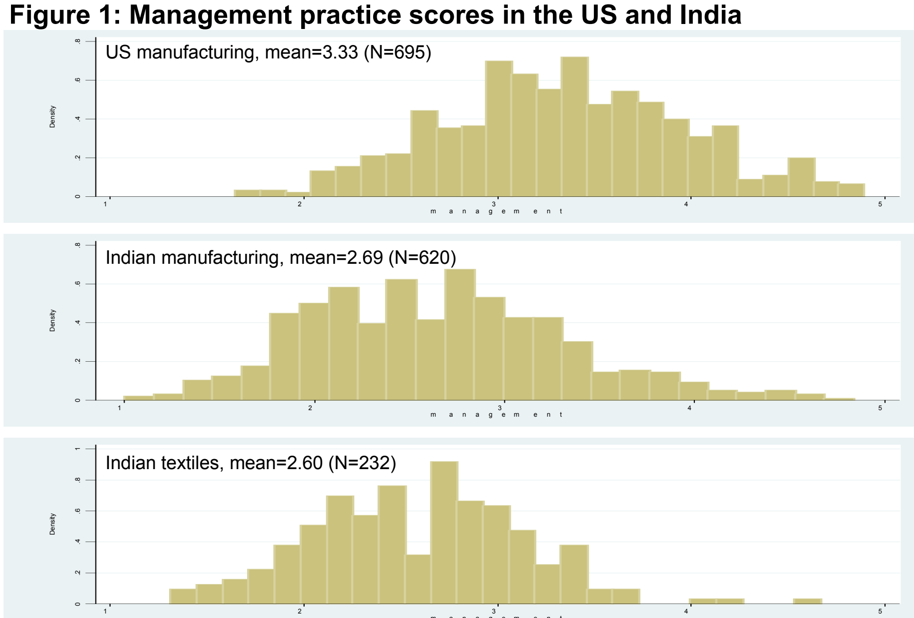
Large room full of repair workers (the day shift)

Workers spread cloth over lighted plates to spot defects

Defects are repaired by hand or cut out from cloth

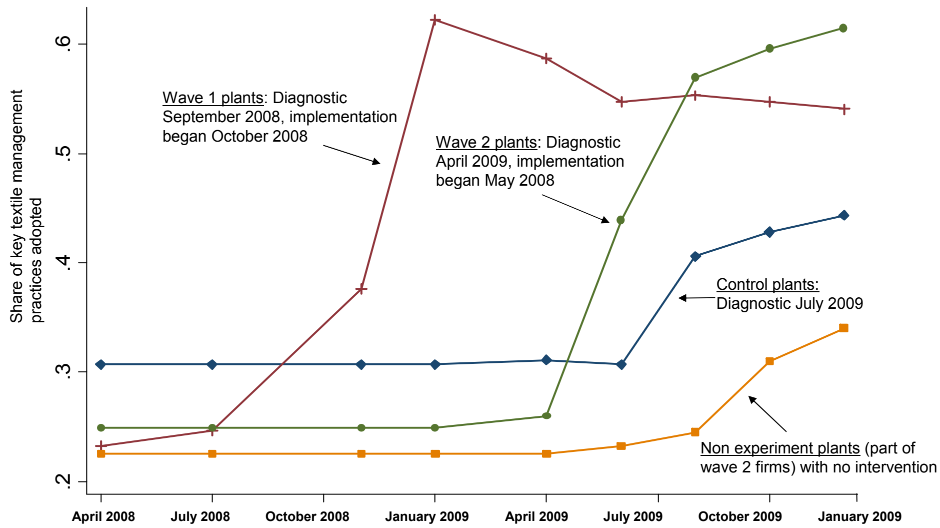
Non-fixable defects can lead to cloth being worthless

Figure 1: Management practice scores in the US and India



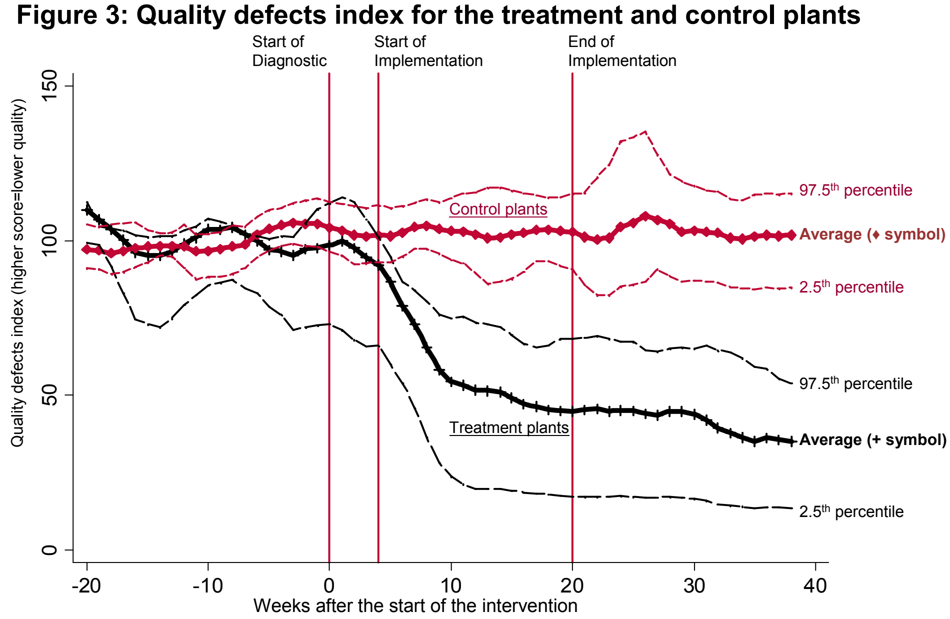
Management practice score firm-level histograms using the Bloom and Van Reenen (2007) methodology and Bloom, Sadun and Van Reenen (2009) data. Double-blind survey tool to evaluate firms monitoring, targets and operations. Scores range from 1 (worst practice) to 5 (best practice), with firm level averages plotted here.

Figure 2: The adoption of key textile management practices over time



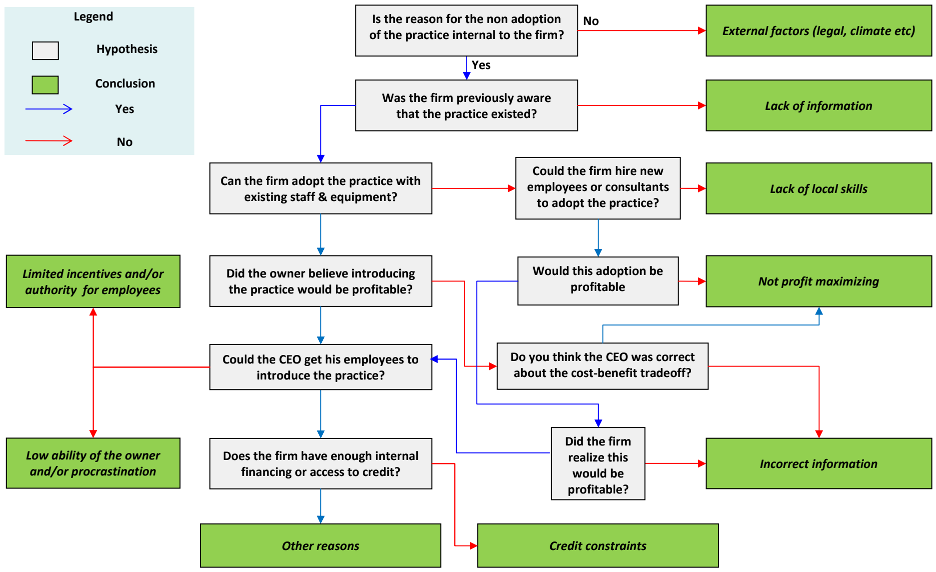
Notes: Average adoption rates of the 38 key textile manufacturing management practices listed in Table 2. Shown separately for the 4 Wave 1 treatment plants (+ symbol), 10 Wave 2 treatment plants (round symbol), 6 Control plants (diamond symbol) and the 5 other plants of the treatment plants (square symbol). Scores range from 0 (if none of the group of plants have adopted any of the 38 management practices) to 1 (if all of the group of plants have adopted all of the 38 management practices). Initial differences across all the groups are not statistically significant (e.g. the initial difference between treatment and control has a p-value of 0.248).

Figure 3: Quality defects index for the treatment and control plants



Notes: Displays the average quality defects index, which is a weighted index of quality defects, so a higher score means lower quality. This is plotted for the 14 treatment plants (+ symbols) and the 6 control plants (♦ symbols). Values normalized so both series have an average of 100 prior to the start of the intervention. To obtain confidence intervals we bootstrapped the plants with replacement 250 times to generate a distribution of outcomes from the treatment and control plants.

Figure 4: Non adoption flow chart used by consultants to collect data



Notes: The consultants used the flow chart to evaluate why each particular practice that had not been adopted in each firm, on a bi-monthly basis. Non adoption was monitored every other month using the tool shown in Figure 4, based on discussions with the firms' directors, managers, workers, plus regular consulting work in the factories. Note that data is only currently available up to 7 months after the end of diagnostic phase in the control firms