Do Managers Matter? A Natural Experiment from 42 R&D Labs in India

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We exploit plausibly exogenous variation in the staggered entry of new managers into India's 42 public R&D labs between 1994 and 2006 to study how alignment between the CEO and middle-level managers affects research productivity. We show that the introduction of new lab managers aligned with the national R&D reforms raised patenting and multinational licensing revenues by 58% and 75%, respectively, and scientist research productivity, including: a 16%, 10%, 11%, and 22% increase in *h*-indices, number of coauthors, publications, and citations per scientist, respectively. Using natural language processing techniques on the set of research abstracts produced among these scientists, we also find that overall mood and sentiment increased by 8.5% following the first managerial change. (*JEL* L22, L23, O32, O33)

1. Introduction

> The greatest leader is not necessarily the one who does the greatest things. He is the one that gets the people to do the greatest things.—Ronald Reagan

Economists have become increasingly aware that compensation schemes (Lazear 2000), organizational design (Bresnahan et al. 2002),

human resource practices (Ichniowski et al. 1997), and management practices (Bloom and Van Reenen 2007; Bloom et al. 2012) are integral determinants of firm-level productivity both within and across countries (Bloom et al. 2015b). Each of these firm-level factors are ultimately shaped, at least in part, by the decisions of specific managers (Bertrand and Schoar 2003). However, how each of these different determinants of firm-level productivity interact with one another is not yet fully understood. Our primary contribution is to exploit a natural experiment to identify the causal effect of the alignment between middle managers and the CEO on organization and individual-level research productivity outcomes.

Even outside business, managers are inherent in every organizational setting, from small villages (Chattopadhyay and Duflo 2004) to policy (Jones and Olken 2005) to science (Azoulay et al. 2010). Especially as ideas become harder to find (Jones 2009) and tasks become increasingly complex (Autor et al. 2003; Caines et al. 2017), managers who can coordinate resources efficiently and focus on core competencies will become even more integral to the success of organizations (Dessein et al. 2016). Simply altering incentives or mandating changes in corporate policy is insufficient for enacting lasting and comprehensive change within an organization. Unfortunately, empirically identifying the causal effects of good managers and their interactions with existing organizational incentives and processes is difficult because better managers are matched to better firms that vary in other unobserved ways (Gayle et al. 2015).

To overcome the usual empirical challenges, we exploit variation arising from the unique institutional features of India's 42 public research and development (R&D) labs comprising >12,500 scientific and technical staff employees. While these labs were created in the 1940s and 1950s, it was not until 1994 that the aim of these labs was transformed with a focus on the commercialization of intellectual property, through the leadership of a new director general, Dr Raghunath Mashelkar. For example, upon entering the office, Dr Mashelkar chaired a committee announcing that 40% of licensing revenues and fees from corporate R&D projects would be shared among scientists. Of the total, 35% would go to innovators, 35% to team members, 15% to other staff involved in the project, and 10% would be shared among all employees of the lab.

Despite the significant strengthening of incentives, we show that the "old generation" of lab managers did not respond by raising inventive activity. Through interviews conducted as "insider econometricians" (Ichniowski and Shaw 2003), we discovered that the old generation of lab managers were opposed to licensing inventions to multinational companies, fearing that the Indian labs would become "labs on rent" for multinationals. Although R&D incentives were *de jure* present, they were not *de facto* followed because lab managers were responsible for authorizing, for example, purchasing decisions for lab equipment and

setting a culture for discovery, undermining the efforts of ambitious young scientists to pursue commercialization of new inventions.

We exploit plausibly exogenous variation in the entry of "new generation" lab managers in these national R&D labs from 1994 to 2006 to identify the causal effect of managerial and CEO alignment on innovation, which we measure through a combination of organizational outcomes, such as patents filed and licensing revenues from multinationals, and scientist outcomes, such as publications and citations. Central to our identification is the bureaucratic process governing the appointment of new lab managers: either at the end of their 6-year employment contract or after they reached the retirement age of 60 years (whichever came first). Moreover, the institutional environment is sufficiently rigid that financial incentives over our sample horizon were not altered, nor did prospective lab managers have discretion to strategically time their self-selection into labs. Under our preferred specification, containing lab- and year-fixed effects, entry of new lab managers is associated with a 58% increase in patents filed and a 75% increase in licensing revenue. Importantly, these improvements in patenting and multinational licensing did not trade off with basic science. Using all the Google Scholar profiles for scientists in these public R&D labs, we find that managerial entry led to a 16%, 11.1%, 10.4%, and 22% increase in scientists' h-index, number of articles, number of coauthors, and number of citations, respectively. Moreover, we feed each scientist's research abstract into a natural language processing (NLP) algorithm to produce a sentiment index of scientist morale in labs, finding an 8.5% increase following managerial entry.

Our paper contributes closely to an emerging literature on the effects of management practices on firm outcomes (Bloom and Van Reenen 2007). Although there is evidence that management practices have positive, causal, and persistent effects on firm productivity (Bloom et al. 2013, 2018) and employee engagement (Hoffman and Tadelis 2017; Makridis 2018), there is scarce evidence on how management practices are embodied in specific lab managers and how these practices interact with other organizational features, like incentive contracts. Our results highlight a theme that was first empirically demonstrated by Ichniowski et al. (1997)—that some human resource practices have a positive effect on organizational outcomes only when paired with other practices. For example, almost analogously to Atkin et al. (2017), who highlight how employee resistance to a new technology for producing soccer balls in Pakistan prevented its adoption despite large cost reductions, we show how resistance among lab managers can stifle the production of knowledge. We also build on Giorcelli (2019), who finds that Italian managers who were exposed to training in the United States adopted similar management practices back home that raised firm productivity.

Our paper also relates to a broader theoretical literature about organizational design and sources of authority in the firm. For example, Aghion and Tirole (1997) distinguish between formal and real authority,

demonstrating how firms might choose to delegate certain decisions in order to maintain real authority. For example, Dessein (2002) shows that managers trade off the loss of control with the loss of information when deciding whether to delegate a task. Through the lens of the public R&D labs in India, we show that lab managers retained the real authority to govern research productivity, even in spite of the national change in incentives by Dr Mashelkar. These managers, however, opted to retain control, leading them to ignore and/or dismiss information and requests from many of the scientists.

Managers play an especially important role in leading by example to cultivate trust (Hermalin 1998). By building trust through repeated interactions with employees (Hermalin 2007), managers earn the respect of employees and serve the important role of aggregating the right information to make strategic decisions for the organization (Komai et al. 2007). This may involve ignoring some information and/or opportunities to focus on the organization's core competencies (Dessein et al. 2016). Unfortunately, managerial biases can also cloud optimal delegation of authority and trust, instead depressing employee performance and absenteeism (Glover et al. 2017).

The structure of our paper is as follows: Section 2 summarizes the theoretical explanations for the role managers play in organizations. Section 3 introduces our data and institutional setting. Section 4 outlines our identification strategy and presents our main causal effects. Section 5 examines a series of robustness exercises. Section 6 concludes.

2. Why Do Managers Matter?

There is a large empirical literature documenting the importance of incentive pay (Lazear 2000), organizational design (Bresnahan et al. 2002), human resource practices (Ichniowski et al. 1997), and management practices (Bloom and Van Reenen 2007; Bloom et al. 2012) as determinants of productivity across not only the private sector, but also hospitals (Bloom et al. 2017), schools (Bloom et al. 2015a), and police forces (Banerjee et al. 2012). However, precisely how these organizational designs are formed and interact with one another remains a black box.

With the exception of Bertrand and Schoar (2003) and Lazear et al. (2015), the literature has been largely silent on the specific role that managers play in formulating corporate policy. Using a unique panel dataset on both executives and the companies they work at over time, Bertrand and Schoar (2003) exploit job-to-job switches to recover manager-fixed effects that they subsequently correlate with firm characteristics, finding, for example, that lab managers with higher performance-fixed effects reside in firms with more concentrated ownership and higher productivity. Lazear et al. (2015) take an alternative approach by looking at a single company with detailed productivity data across employees in teams with different managers, finding that higher quality managers not only raise

employee productivity, but also retain employees who may otherwise exit the firm. Taking a related personnel approach by looking within a high-tech firm, Hoffman and Tadelis (2017) use employee survey responses to measure managerial quality and subsequently show that better managers reduce turnover and raise engagement. Similarly, Makridis (2018) shows that managerial quality plays an important role in shaping perceptions of corporate culture and employee engagement across firms.

Our theoretical starting point is that good lab managers produce better organizational outcomes (Bloom et al. 2015b), raising productivity in at least two ways. First, managers help allocate resources to their most efficient use within an organization. Dating back at least to Coase (1937), firms are unique because prices do not exist as a rationing device. The absence of prices creates a challenge for allocating resources and signaling scarcity among divisions and employees. However, managers fill this void by incorporating information and commanding resources (Komai et al. 2007): formally through company policy and informally through persuasion (Hermalin 1998) that is bolstered through repeated interactions that can foster trust (Hermalin 2007).[1]

Second, managers can influence employee engagement and productivity by promoting cultural norms within an organization (Van den Steen 2005, 2010). Since managers are arguably the "face of an organization," they have the opportunity to formally articulate policy and lead by example. When a firm has a culture of openness, charismatic managers who can empathize with their employees can raise engagement and innovation (Rotemberg and Saloner 1993). Visionary managers also influence the composition of projects and employee incentives that are implemented (Rotemberg and Saloner 2000). Especially in uncertain environments, managers with strong beliefs can provide the needed incentives for coordinating efforts (Van den Steen 2005). Conversely, managers with biased priors can also negatively impact employee and organizational performance (Glover et al. 2017). Ultimately, however, different types of managers can play different roles in organizations—that is, sometimes executives with more leadership capabilities can raise firm productivity, whereas other times an organization may simply need executives with more managerial and logistical capabilities (Bandiera et al. 2018).

A related explanation for the impact of managers is their formulation of relational contracts: "informal agreements and written conducts of conduct that powerfully affect behaviors of individuals within firms" (Baker et al. 2002). Especially when the actions of an agent are unobserved, but the outcomes are observed and noncontractual, relational contracts can promote self-enforcing long-run benefits. Consider, for example, a scientist tasked with producing good research. While the actions are unobserved, the outcome (e.g., publication or licensing revenue) is observed.

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1. See Van den Steen (2009) for a comparison of the costs and benefits of authority versus persuasion in the firm.

However, the principal usually has no vehicle for contracting over the outcome—that is, writing into the contract a requirement to publish in a certain location or obtain a certain amount of licensing revenues. Bosses may also decide to delegate their authority to middle-level managers because they have access to more local information (Baker et al. 1994)—as is the case with these public R&D labs where middle-level managers retain considerable discretion. However, relational contracts take time and are tough to develop, particularly since they require relational knowledge and alignment between the managers and employees (Gibbons and Henderson 2012).

However, managers do not make decisions in isolation—they interact with a broader web of organizational forces. For example, there is a large literature on how the provision of incentive contracts (e.g., performance pay) affects worker productivity (Lazear 2000; Paarsch and Shearer 2000), effort (Paarsch and Shearer 1999; Shearer 2004), and human capital formation (Shaw and Lazear 2008; Makridis 2019). Our paper shows that even if the right incentives are in place, managerial alignment across the hierarchy matters significantly for understanding organizational productivity. In particular, though scientists are given stronger incentives to patent and publish, they may fail to do so because middle-level lab managers prevent them from acquiring the relevant equipment to conduct research. Until these managers exit, the effects of incentives may be muted.[2]

3. Institutional Setting and Data

3.1 Institutional Setting

We study the entry of new lab managers across India's 42 state-owned national labs under an autonomous umbrella organization, the Council of Scientific and Industrial Research (CSIR), which has a federal mandate of promoting public science and research. Collectively, these labs employ 12,500 scientific and technical employees, spanning all major scientific and engineering disciplines. While they were founded in the 1940s and 1950s, their main objective until the 1980s was to indigenize imported technologies, such as tractors, food processing, pharmaceuticals, and polymers. We now discuss how these aims changed in the years that followed.

3.1.1 New Leadership to Govern the National R&D Labs.
A large lab managerial transformation took place in 1994 as a new director general, Dr. Raghunath Mashelkar, entered leadership with responsibility over

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2. In an earlier version of the paper, we developed a simple principal–agent model that shows how misalignment between the principal and manager can obstruct productivity. For example, if the lab manager has a taste for domestic over foreign output that the principal does not also have, then the lab manager will overallocate effort toward the domestic output, reducing aggregate productivity.

all 42 labs. Dr. Mashelkar had strong views about the importance of commercializing intellectual property, exemplified through several speeches delivered during the year and through the "CSIR 2001 vision document" published in January 1996. Integral to his strategy was the ambitious goal of reducing dependence on government budgetary support and promoting innovation, which coined the phrase "patent, publish, and prosper" based on his view that "patents are wealth creators."[3] One of the reasons Dr. Mashelkar was particularly suited for his new responsibility was that he had great success in securing US patents on polymers and licensing these patents to multinationals, like General Electric (GE), while serving in a CSIR lab based in Pune (National Chemical Laboratory [NCL]). During those years, Dr. Mashelkar traveled to the United States to foster engagements with GE. For example, his lab had 88% of the foreign patents granted to all 42 labs by 1994.

Despite Dr. Mashelkar's success in developing patents and licensing revenues with multinationals at NCL, replicating this on a broader scale across the other 41 labs would not be easy. For example, scientists' salaries are determined by India's central government rules, meaning that CSIR management had no scope to adjust incentives by modifying these salaries for individual scientists (e.g., to reward talent). In particular, salaries for all government employees in India are determined centrally by the Central Pay Commission, and the CSIR management was required to reimburse scientists at the pay scales determined by this commission. Throughout the course of our study, *there are no salary revisions*. The fact that compensation policy is held fixed during the sample is critical to our identification since changes in managers and management practices are often accompanied by changes in compensation policy (Bloom and Van Reenen 2011), which feeds back into employee productivity.

Given that these incentives for lab employees were ineffective and the incentives for lab managers could not be adjusted through the Central Pay Commission, new appointments were the only vehicle through which Dr. Mashelkar could modernize the national labs. In particular, incumbent lab managers could be replaced only if they ended their 6-year contract terms or retired by reaching age 60 years. We spoke with representatives from each one of the CSIR labs and confirmed that these bureaucratic rules were enforced in each of the labs in the sample. For example, consider Dr. B. Chandrasekaran, director of CSIR-Central Leather Research Institute. While beginning as a senior research fellow from 1986 to 1988, Dr. Chandrasekaran advanced to various scientist ranks and eventually chief scientist and lab director. In this sense, as these incumbent scientists joined without knowledge of Dr. Mashelkar's rise CSIR director, their current tenure in the lab provides plausibly exogenous variation in the timing of new lab managerial changes. We examine this underlying assumption in greater detail later.

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3. http://www.socialcause.org/getarticlefromdb.php?id=149.

3.1.2 New Incentives to Compensate Scientists.   India's national labs traditionally had a policy of sharing licensing revenue with individual inventors until this policy was discontinued on September 1977.[4] However, upon Dr. Mashelkar's entry in 1994, a committee chaired by him on June 15 announced that 40% of licensing revenues and fees from corporate R&D projects would be shared among scientists.[5] Of the total remuneration, 35% would go to innovators, 35% to other team members, 15% to indirectly involved staff, 10% would be shared among all employees of the lab in question, and 5% would go to a fund to promote socially responsible projects.[6] Although CSIR was still constrained by the Central Pay Commission (salaries could not be adjusted), Dr. Mashelkar found an indirect way of remunerating productivity among scientists: rewarding those who successfully commercialized technologies.

Traditional wisdom is that the change in incentives would raise productivity and licensing revenues. For example, using personnel data from Safelight Glass Corporation, Lazear (2000) documents a rise in employee productivity following a shift toward performance pay; for additional examples, see Paarsch and Shearer (1999) among tree planters and Bandiera et al. (2005) among strawberry pickers. However, the same gains in productivity observed in prior settings were not observed in these national R&D labs. Although lab managers had no flexibility in increasing government budgetary support for their lab, they had full responsibility over the authorization of resources toward projects that had higher likelihoods of being commercialized.

During the years that followed, Dr. Mashelkar was able to appoint new lab managers at 36 of the 42 laboratories.[7] While the "new generation of lab managers" entering labs directed resources toward IP commercialization, the "old generation of lab managers" fundamentally disagreed with the aim of licensing with multinationals and wanted to remain dependent on government support, fearing that CSIR would become a "lab on rent" for multinationals (see Appendix Section A.1).[8] In fact, Dr. Mashelkar

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4. CSIR circular 9/203/92-TU, May 8, 1992.

5. CSIR letter 9/203/94-TU, June 15, 1994.

6. Is this big or small? We have data on 156 patents licensed from 2001 to 2006, and the average remuneration to an individual inventor is approximately $2,200. Even this modest dollar amount works out to about 40% of the average senior scientist's 1999 annual salary.

7. We tracked every lab managerial change at these labs from 1994 to 2005. We explored why six of the labs did not experience a director change and found various reasons: four labs were merged into other labs as a result of organizational restructuring, one lab ceased to exist, and the last was used for human capital development and information aggregation for the organization (thus not participating in active research).

8. For example, Dr. Mashelkar is quoted in an interview candidly discussing these challenges in persuading middle-level managers. "After my speech, Dr. Shankar stood up and angrily shot back, saying we would corrupt ourselves if we went down the road I was suggesting. It was a free and frank dialogue. The same scientist, exactly two years later during another visit to CMB, came to inform me that he had developed a breakthrough for which we had received a US patent. He sensed it could make pots of money and wanted to know how

faced internal criticism for being on a World Intellectual Property Organization (WIPO) panel and advocating for product patents, with critics claiming that licensing to multinationals would lead to an "astronomical increase in the prices of agro seeds and pharmaceutical medicines."[9] Attitudes among the old generation lab managers reflected the prevailing angst about multinationals behaving rapaciously in poor countries. Our interview evidence indicates that these attitudes prompted lab managers not to authorize funds for scientists within their labs and suppress a culture of research productivity through either patenting or publishing.

3.2 Data and Measurement

Our data come from all 42 national R&D labs that are part of the CSIR, containing information on patent filings and patent grants, revenue from multinationals, government budgetary support, and lab characteristics and location all from 1994 to 2006 during Dr. Mashelkar's tenure as director. We also collected the curricula vitae (CVs) from 61 lab managers across 36 labs and the CVs from more than 500 senior scientists and gathered each scientist's Google Scholar profile. Our fieldwork-based data collection is in the tradition of insider econometrics introduced by Ichniowski and Shaw (2003). One limitation of our data is that we cannot include years prior to 1995 in our sample. Since patenting was driven almost exclusively by one lab prior to 1995, we would have no variation in our outcome variable.

Raising the number of foreign patents was a national priority for innovation because the Indian patenting process was not well regarded. For example, patent reviewers infrequently had domain expertise, meaning there was little quality control and, therefore, little incentive to develop novel technology that was marketable to multinationals. The existing stock of technology and knowledge was largely indigenous, developing, for example, agricultural innovations that were applicable only to indigenous Indian agriculture. To motivate the significance of managerial entry, Figure 1 plots the number of patent applications from 1960 to 2016. Remarkably, patenting applications are nearly flat from 1960 to 1990, before surging in 1994, which coincided with the entry of new managers. For example, from 1990 to 2010, patenting applications among nonresidents (residents) grew by 1056% (672%).

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one determines the royalty to be charged, how can one convert the discovery into a business proposition. In fact, this did become a business proposition. Real triumph was exactly 1 year after that, when we gave him the Technology award. He also received the Bhatnagar award, which is the highest prize that you can get in the field of science in India. The man who got both the Bhatnagar and Technology award was the same man who 3 years earlier just did not believe in my philosophy! In Dr. Mashelkar's case, he discovered that he could be a "corporate scientist" without sacrificing the cause of pure science" (http://www.rediff.com/money/2005/mar/24spec.htm).

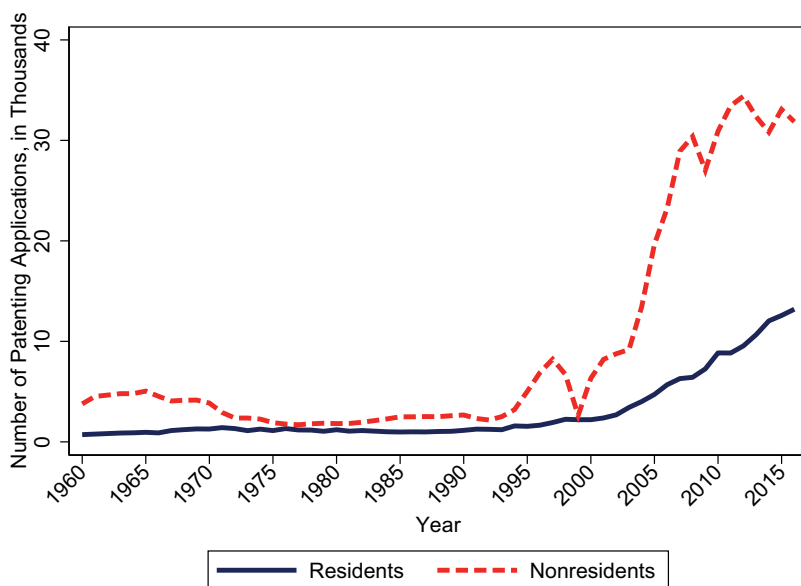9. http://www.outlookindia.com/printarticle.aspx?233803.

Figure 1. Patenting Applications Among Residents and Nonresidents, 1960–2016.
Notes: The figure plots the number of patenting applications from residents and nonresidents. Patent applications are worldwide patent applications filed through the Patent Cooperation Treaty procedure or with a national patent office for exclusive rights for an invention.
Source: WIPO, WIPO Patent Report: Statistics on Worldwide Patent Activity.

Table 1 documents several descriptive statistics in the baseline dataset across two (arbitrary) periods of time. We find that revenue from multinationals grew dramatically from 1995 to 2006, over a factor of 11. Meanwhile, funding from the government in these labs changed only marginally. Importantly, patents granted grew not only in India, but also, and much more so, in the United States and abroad. For example, patents granted by the United States grew from roughly 0.67 patents per scientist to 3.39, whereas abroad more generally they grew from 0.98 to 6.04. Despite all these significant increases in patenting, the composition of scientists in these labs did not change in any meaningful ways. For example, the number of awards granted to scientists, number of countries visited among scientists, the share of scientists with a PhD, or share of scientists who visited the United States each stayed constant in 1994–2000 and 2001–2006. The invariance of these composition characteristics reflects the fact that the composition of entrants into the senior scientist position did not change, although new hiring may have occurred at more junior levels of these labs.[10]

10. Appendix Section A.1 provides a more targeted examination of these managers. While they tend to have more patents (from their time serving as scientists in the labs) and more

Table 1. Descriptive Statistics, 1994–2006

	Full sample		1994–2000		2001–2006	
	Mean	SD	Mean	SD	Mean	SD
Outcomes						
Revenue from multinationals	106.4	186.7	67.0	156.8	132.7	200.4
Revenue from government	505.6	697.1	419.9	746.5	592.0	633.5
Patents granted, United States	1.80	4.68	0.67	2.35	3.39	6.33
Patents granted, abroad	3.51	7.53	0.98	2.91	6.04	9.60
Patents granted, India	5.09	9.34	3.31	5.51	6.88	11.75
Scientists						
Awards among scientists	0.30	0.25	0.30	0.25	0.30	0.25
Countries visited among scientists	0.41	0.21	0.41	0.21	0.41	0.21
Fellows in Indian Science Association (%)	0.12	0.25	0.12	0.25	0.12	0.25
Scientists with PhD (%)	0.79	0.18	0.79	0.18	0.79	0.18
Scientists visit to United States (%)	0.46	0.21	0.46	0.21	0.46	0.21
Cumulative patent citations	1.77	2.26	3.12	3.20	1.19	1.37
Publication impact factor	97.9	153.9	65.6	95.1	129.7	190.2
Observations	502		251		216	

Notes: The table reports the means and standard deviations of important measures of innovative activity and the labor force in the national R&D labs. Revenue from multinationals and the government refers to average lab revenues used for financing research and other activities. Patents granted refers to average patenting among scientists in the labs. The remainder of the variables refers to more detailed characteristics about the scientists. All nominal variables are in Rs crore, where crore represents $10 million.
Source: CSIR, 1994–2006.

4. Quantifying the Contributions of Lab Managers

4.1 Empirical Specification and Identification

Our baseline statistical model relates outcomes among either individual scientists, denoted *i*, or labs, denoted *l*, over time, denoted *t*, with the entry of a new lab manager:

$$y_{ilt} = \gamma \text{MGMT}_{lt} + \beta X_{it} + \phi_{I,l} + \lambda_t + \epsilon_{it}, \tag{1}$$

where *y* denotes our outcome of interest, MGMT denotes an indicator for whether the new lab manager has entered the lab, *X* denotes a vector of lab-level controls (such as funding from the government and funding from industry), and ϕ and λ denote fixed effects on individual scientists/labs and year, respectively. We cluster standard errors at the lab level to allow for arbitrary degrees of autocorrelation within a lab over time (Bertrand et al. 2004).

We focus on several outcomes of interest. Our first set of outcomes— namely patent filings and licensing revenue—varies over time, across labs. If, for example, new lab managers aligned with Dr. Mashelka's vision of

experience traveling to different countries, they do not systematically differ in other types of human capital measurements. In this sense, the differences among these new generation managers reflect alignment with Dr. Mashelkar's vision for the CSIR labs.

patenting and licensing enter the labs, we should observe an increase in their research activity and licensing to multinationals. Our second set of outcomes varies over time across individuals. As we will explain in more detail shortly, we gathered data on every scientist within these labs, tracking not only traditional quantitative metrics of research activity (e.g., publications, citations, *h*-index, coauthors), but also new metrics, such as scientific sentiment and the introduction of new scientific techniques. We examine these outcomes in response to lab managerial changes to understand whether basic scientific research also improves. Moreover, the fact that we control for government and industry funding over these years ensures that we are not attributing variation in research outcomes to differences in the availability of funding.

Our identification of γ is based on plausibly exogenous variation in the entry of new lab managers into India's public R&D labs based on the institutional rules that govern new appointments. New lab managers are appointed if and only if they reach the end of their six-year contract or if the incumbent lab manager reaches retirement at 60 years old (whichever comes first). In this sense, our identification comes from the fact that different cohorts of lab managers were appointed to their positions at different points in time for reasons that are orthogonal to contemporaneous scientist and lab-level outcomes. Importantly, although the parent organization (CSIR) that appointed new lab managers had no control over the timing of lab managerial replacements, they did have control over who would be appointed when the time came, such that only lab managers who agreed with Dr. Mashelka's new vision were approved to head the labs.[11] Moreover, there is no correlation between managerial quality and their distance from the lab.

Even if the timing of managerial entry is random, one potential concern with our identification strategy is that more productive scientists are matched into better labs, meaning that the increase in innovation outcomes merely reflects a selection effect. That nonrandom matching could happen in two related ways. First, scientists could strategically sort into better labs. Second, while the institutional setup makes it unlikely and difficult for Dr. Mashelkar to select particularly high performing managers and assign them to particularly high performing labs to create

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11. One of the ways we validate this assumption, in addition to our interviews and knowledge of the institutional process, is by coding the career histories of 199 lab managers appointed from 1981 to 2017, for whom any information was available in online archives. Of these 199 lab managers, 44 managers predate Dr. Mashelkar and 155 lab managers were appointed after Dr. Mashelkar took charge of CSIR. In the pre-period, the mean value that a lab manager is a CSIR career scientist (i.e., only ever worked at CSIR labs and was employed by the lab at the time of being lab manager) was 0.45. In the post period, the mean value that a lab manager is a CSIR career scientist (i.e., only ever worked at CSIR labs and was employed by the lab at the time of being lab manager) was 0.63. These results show that the probability a lab manager was a career scientist at CSIR is actually higher, not lower, in the post-period, strengthening our identification strategy.

momentum, strategic selection is still theoretically possible. We examine both these possibilities.

First, the institutional setting is such that prospective lab managers would not have been able to anticipate vacancies in labs well ahead of time. Moreover, because each of the CSIR labs has a particular research focus, these prospective lab managers would have had to not only anticipate vacancies, but also choose their area of specialization on the basis of their forecast. However, the bulk of individuals who sort into basic science research do so because of their taste for the discipline, rather than for financial compensation (Stern 2004). We conducted field interviews, finding that most of the managers in these labs were career scientists within the lab—that is, conditional on becoming a manager, they had already invested upward of 20 years in the lab. Moreover, consistent with the qualitative evidence, we find that managerial quality proxied by the average impact factor for each scientist prior to becoming a manager, and lab quality, proxied using government funding for the lab, have a very weak correlation of 0.04.

Second, we collect the CVs of 61 lab managers, identifying whether the new lab managers have any ethnic, educational, or professional ties with Dr. Mashelkar. We also construct an affinity index by averaging across these three characteristics. As long as the affinity between Dr. Mashelkar and each lab manager prior to 1994 was exogenously determined (which we described above in our discussion of the institutional process), then we can simply compare affinity scores for pre- and post-lab managerial affinity. Out of the 17 changes for which we have information, we found that affinity scores declined for four cases following the lab managerial change, increased for two cases, and stayed the same for 11 cases, suggesting that unobserved differences in lab managerial affinity with Dr. Mashelkar cannot account for these effects.[12]

While the power of our statistical exercise is limited by the sample size we have access to, we found strong qualitative support that complements our affinity index. For example, in an interview, Dr. Mashelkar recounted his experience hiring new managers. "There was one person at my headquarters. I tried my best to make him come up to a particular level but it simply was not working. I shifted him regardless of his political connections, because at the end of the day, CSIR is an Rs 12,000 crore (Rs 120 billion) organization."[13] In this sense, while there was an inclination to make some hires based on personal connections, ultimately the hiring decisions were based on an alignment between vision and the manager's willingness to execute on it. In this sense, we interpret γ as the causal effect

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12. One might also be interested in evidence of heterogeneous treatment effects of managerial entry based on the affinity index. While we are limited by statistical power to say conclusively, we do not find evidence of heterogeneity along this dimension, which is not surprising since the index is largely uncorrelated with managerial entry.

13. http://www.rediff.com/money/2005/mar/24spec.htm.

associated with new managerial entry when there is alignment between CEO and managerial vision for scientific research.

4.2 Lab-level Results

We begin by examining how managerial entry affects lab-level outcomes, such as patenting and licensing revenue from multinationals. Table 2 documents these results. Under our preferred specification in Columns 2 and 4, where we control for lab- and year-fixed effects, we find that managerial entry is associated with a 57.6% increase in patents filed abroad and a 75% increase in licensing revenue from multinationals.[14] Not surprisingly, failing to control for time-invariant differences across labs produces upward-biased estimates since Dr. Mashelkar may prioritize appointments of new managers in more productive labs—for example, those scientists who demonstrate greater patenting and licensing potential.

Does the surge in patents filed abroad trade off with patents filed in India? While we do find that managerial entry is associated with an 11.2% decline in patents filed in India, it is very imprecise, with a p-value of 0.437. A test of the null hypothesis that managerial entry is associated with a null effect on patents filed in India produces an F-statistic of 0.62 and p-value of 0.437, meaning that we fail to reject the null that there was no trade-off with domestic output. As we discuss shortly, we also document a systematic rise in research productivity among scientists in labs that are exposed to new lab managers aligned with Dr. Mashelkar's vision.

Appendix B presents results where we examine heterogeneity in treatment effects over time—that is, looking at the response of patenting and licensing revenues years before and years after managerial entry. Consistent with our discussion of the institutional setting, we do not find evidence of pre-trends, and we find that the effects of managers on lab outcomes grow over time. Appendix C discusses the results from a series of interviews with CSIR executives about the impact of international patenting on foreign investment. We learned that the shift in priority toward patenting and commercially viable technologies allowed the labs to secure several large sources of foreign investment early on by, for example, GE. Appendix B also shows that citation-weighted

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14. We focus on patents filed abroad in period $t + 1$ to allow for a lag between the introduction of a new manager and their approval of research ideas for submission into the patenting process. We also focus on licensing revenues from multinationals in period $t + 2$ to allow for a longer lag due to the process of international contracting with multinational companies. Our results are qualitatively robust if we focus both outcomes in period $t + 1$ on period $t + 2$. For example, the gradient on managerial entry for licensing revenues in $t + 1$ is 0.303 (p-value = 0.440). Similarly, the gradient on managerial entry for patents filed abroad in $t + 2$ is 0.321 (p-value = 0.237). Unfortunately, we cannot track all the specific patents that are being produced, which would otherwise allow us to conduct a textual analysis of the language and topic areas covered in patents. However, the fact that licensing revenue rises suggests, through revealed preferences, that these are meaningful patents.

Table 2. The Effects of Managerial Changes on Lab Outcomes, 1994–2006

Dep. var.=	log (Patents filed abroad $t+1$)		log (Licensing revenue $t+2$)	
	(1)	(2)	(3)	(4)
1[post management change]	1.13***	0.58*	1.41***	0.75**
	[0.25]	[0.29]	[0.32]	[0.33]
R-squared	0.16	0.73	0.22	0.65
Sample size	366	366	259	259
Controls	Yes	Yes	Yes	Yes
Lab FE	No	Yes	No	Yes
Year FE	No	Yes	No	Yes

Notes: The table reports the coefficients associated with regressions of logged foreign patent filings in period $t+1$ and logged revenue from multinationals in period $t+2$ on an indicator for the year and years after a new lab manager enters, controlling for lab- and year-fixed effects and logged government and industry funding support. Standard errors are clustered at the lab level.
*** denotes 1%, ** denotes 5%, and * denotes 10% significance.
Source: CSIR, 1994–2006.

publications grew significantly, meaning that these patenting innovations did not come at the expense of basic research.

How do these results compare with other related public sector reforms that have been studied? Similar to Gagliarducci and Nannicini (2013), who find that the main effect following the introduction of higher pay among Italian municipal governments was the attraction of new and more educated politicians, our results highlight a new dimension of selection effects—the alignment between the CEO and middle-level lab managers. Moreover, like Martinez-Bravo (2014), who find that the quality of incumbent appointed officials in Indonesia before their political transition are a key determinant of democratic outcomes, we find that incumbent lab managers who did not share the same vision as Dr. Mashelkar stifled patenting and licensing in their labs.[15]

However, the importance of selection effects does not discount the crucial role incentives play. For example, Muralidharan and Sundararaman (2011) find that teachers in Andhra Pradesh (India) respond to performance pay incentives by improving effort and delivery of educational services to their students. Duflo et al. (2012) find similar results in an entirely separate experimental setting in India. To understand the relative effectiveness of incentives versus selection effects, we argue that one must understand the hierarchy within an organization. In many of these experimental settings with teachers, for example, the link between compensation and productivity was made explicit through the introduction of incentives. In contrast, scientists in India's public R&D labs depend crucially on their

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15. There is, of course, a broader literature of interventions in developing countries, including surrounding management practices on manufacturers (Bloom et al. 2013), educators (Bloom et al. 2015a), and the civil service (Rasul and Rogger 2018).

lab manager's discretion to approve requests for equipment and promote a culture of discovery and publication. In this sense, our results are consistent with the well-known link between effort and productivity: Incentives work only when the actions by the agent actually influence their observed output (Prendergast 1999).

4.3 Scientist-level Results

We now turn toward our microeconomic impacts on research productivity among individual scientists over time. Here, our results are identified off changes in the way individual scientists respond to different lab managers over time. Drawing on Google Scholar, we search for every scientist in the available public R&D labs and obtain several metrics on their research productivity over time, such as their number of coauthors, number of articles published, number of citations, and h-index, producing a longitudinal panel for 595 scientists contained in these labs. These metrics are important for gauging the potential trade-off that new lab managers may have had on the production of basic scientific research.

We also introduce two new measures aimed at quantifying the impact of managerial entry on scientists' morale and access to resources. First, after obtaining every research abstract from scientists in these labs, we feed the text into an NLP algorithm whereby words are parsed into positive or negative emotions, which we aggregate into an annual sentiment index for each scientist. While we leave the details of our measurement approach to Appendix A (together with examples of words that contribute to positive versus negative sentiment), our approach is based off of recent innovations from the psychology literature that have crowdsourced lexicons over eight primary emotions: anticipation, fear, joy, sadness, trust, disgust, surprise, and anger (Jockers 2017). Each word in an abstract is classified as positive, negative, or neutral; we aggregate across these words in each abstract for a given scientist and publication year to obtain an overall sentiment score.[16]

Second, to better gauge the impact of managerial entry on resource allocation, we construct a measure of scientific creativity by counting the number of techniques that scientists use to describe their research based on the hypothesis that the number of distinct techniques is a

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16. We document a list of the most common positive and negative sentiment words in Appendix A. While our baseline results are identified off of all these words because they are included in the state-of-the-art psychology literature NLP models, our results are robust to excluding different words that are potentially more ambiguous, like "reserve." Moreover, we also conducted a crowdsourced survey on Amazon MTurk where 100 human coders were asked to code the sentiment of 100 randomly selected words. We found that words our NLP codes as positive sentiment are 0.78 percentage points more likely to be coded as positive by the MTurk coders, controlling for the average confidence associated with each words. These results suggest that our NLP is detecting meaningful and reliable differences in sentiment across words.

proxy for the resources available for research.[17] Because scientists describe their methodology (which includes relevant scientific instruments or techniques) in their abstracts, our thinking is that identifying the use and discussion of these terms is informative for understanding resource allocation within labs. If alignment between Dr. Mashelkar and new managers is associated with better resource allocation and funding of new scientific developments, then we should observe a rise in the number of techniques that scientists use because they are able to make the required purchases to conduct the experiments of interest.

While we recognize that both measures of interpersonal collaboration/morale and creativity are imperfect, they are ultimately proxies that we believe are capturing meaningful variation in these labs over time. Our specific outcomes in the regressions that follow take the $t + 2$ lead given the time involved in taking a scientific idea to publication (and eventual citation). To ensure that our specification of the outcome variable is not random, we tested alternative timing structures. Even though we find a positive association between time t or $t + 1$ outcome variables and the managerial change, our results are most statistically significant under the $t + 2$ specification.

Table 3 documents our main results for these scientist-level outcome variables. While we focus on contemporaneous changes in sentiment and number of techniques used since these are more real-time and dynamic measures of scientific attitude and creativity, we look at how lab managerial changes in period t affect research productivity in period $t + 2$ since there is likely to be a delay between new lab-level investments and the publication process. Beginning with our naive least squares estimator in the odd-numbered columns, we find that the entry of new lab managers is associated with a systematic increase in research productivity across the board: improvements in sentiment, the quantity and quality of publications, collaboration among coauthors, and ingenuity with the techniques used in research. For example, sentiment rises by 20.1% following the entry of a new lab manager and scientists' h-index rises by 33.5%.

Turning to our fixed effects estimator in our even-numbered columns, we find that lab managerial entry is associated with an 8.5% rise in scientific sentiment and a 3.5% increase in the number of new techniques used in conducting research, although the latter is not statistically significant at conventional levels. Although we were also concerned at first about our ability to create reliable proxies of scientific sentiment and creativity, the fact that we detect statistically and economically significant effects suggests that the abstracts contain enough identifying variation—that is, to the extent the abstracts simply contain noise, we would obtain null

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17. We used two aggregations of information online to produce this list of dictionary terms: https://en.wikipedia.org/wiki/Category:Laboratory_techniques and https://en.wikipedia.org/wiki/Category:Scientific_techniques.

Table 3. The Effects of Managerial Changes on Scientists, 1994–2006

Dep. var.=	log (Sentiment)		log (H-index $t+2$)		log (Number of articles $t+2$)		log (Number of coauthors $t+2$)		log (Number of citations $t+2$)		log (Number of techniques)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
1 [post management change]	0.201***	0.085*	0.335***	0.160**	0.181***	0.111*	0.209***	0.104**	0.540***	0.220	0.137***	0.035
	[0.040]	[0.043]	[0.101]	[0.074]	[0.054]	[0.058]	[0.049]	[0.048]	[0.159]	[0.135]	[0.035]	[0.037]
R-squared	0.02	0.40	0.01	0.70	0.01	0.69	0.01	0.55	0.01	0.66	0.01	0.59
Sample size	4595	4595	4702	4702	4702	4702	4702	4702	4702	4702	4702	4702
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Person FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Year FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Notes: The table reports the coefficients associated with regressions of different scientist outcomes on an indicator for whether the first lab managerial change has taken place, conditional on lab controls, including funding from the government and from industry that the research lab might receive. We focus on six different outcomes: (1) sentiment in period t, which is generated by feeding in all the words in scientists' abstracts into the R package syuzhet, (2) H-index in period $t+2$ (measure of a scientist's publication impact), (3) logged number of research articles produced in period $t+2$, (4) logged number of coauthors in period $t+2$, (5) logged number of citations for articles published in period $t+2$, and (6) logged number of new techniques used in the research in period t. For discussion of the construction of outcomes (1) and (6), see the main text. Standard errors are clustered at the lab level, and no weights are used.
*** denotes 1%, ** denotes 5%, and * denotes 10% significance.
Source: CSIR, 1994–2006.

associations.[18] We also find widespread evidence that research productivity along traditional margins increases. For example, lab managerial entry is associated with a 16% increase in scientists' *h*-index, 11.1% increase in scientists' publication of new articles, 10.4% increase in the number of coauthors among scientists, and 22% increase in the number of citations. Even though the variation in the timing of managerial entry is quasi-random, it is still possible that upward bias exists if Dr. Mashelkar chose to introduce new managers in better labs sooner than for others. By controlling for time-invariant heterogeneity, we purge variation in scientific outcomes that might explain systematically better performance among one scientist over another.

Similar to our earlier lab-level results, one concern might be that our effects on observed dimensions of research productivity are resulting from a trade-off from other unobserved allocations of time or investment. First, we have purposefully collected a comprehensive set of scientist-level measurements that reflect productivity, rather than just a single component of productivity (e.g., publications). To the extent scientists are trading off time or investment in other forms of productive research, they would have to be negatively correlated with these observed measures of productivity, which seems unlikely. Second, since our specifications include person-level fixed effects, we are exploiting movements in research productivity within-person, before versus after the arrival of a new manager in their lab. That means researchers who do not publish much over the entire sample are not used to identify our causal effect—identification is coming from changes in research productivity for a given scientist in response to the arrival of a new manager. In this sense, our results suggest a change in both the quantity and quality of research among scientists: a reorientation toward more creative research and an acceleration of existing research.

5. Robustness Exercises

5.1 Hawthorne Effects

Do our results simply reflect a "Hawthorne effect" whereby employee morale rises after a change, even if the change does not have a causal effect on underlying performance or productivity? While these effects generally have little empirical support (Levitt and List 2011), we can formally test whether they are present here by leveraging the fact that some labs exhibit more than one managerial change from 1991 to 2010. Regressing logged sentiment on an indicator for the first and second managerial

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18. Moreover, consistent with these results using proxy variables, Appendix C provides causal evidence of diffusion in managerial practices based on the success of the NCL lab. In particular, after Dr. Mashelkar illustrated the beneficial effects of science-driven research and multinational patenting, other labs began to pursue joint projects with NCL under the NCL–IICT model. These partnerships are concentrated in labs following the entry of new managers. We find statistically significant effects of these joint projects on the mix of patents and patenting with multinationals.

change, conditional on controls and scientist and year-fixed effects, produces gradients of 0.081 (p-value = 0.074) and -0.03 (p-value = 0.525).[19] Moreover, even if we do not control for the first managerial change, the gradient on the second managerial change is -0.062 (p-value = 0.206). We find similar null associations when we focus on our lab-level outcomes (see Appendix B). We conclude that our causal effect of managerial entry on scientific productivity is coming from changes introduced by the first new generation lab manager.

5.2 Timing of Managerial Changes

We turn toward a more explicit examination of our identifying assumption—that bureaucratic rules governing the entry of new lab managers affect lab outcomes only through their effects on the entry of lab managers into the lab. We conducted multiple interviews with employees across labs and the CSIR headquarters and conducted supplementary searches to corroborate the stated governance rules that incumbent lab managers would exit only if their contract term ended or they retired by reaching age 60 years. We also regressed the timing of lab managerial change on government budgetary support, number of patents, and number of publications within each individual lab, and we did not find a correlation. These diagnostics show that the timing of lab managerial changes is exogenous with respect to real outcomes in the scientific productivity of these labs.

5.3 Other Possible Confounding Policies

One additional concern is that lab managerial changes coincide with other policies and/or unobserved shocks to lab outcomes. Put differently, while the timing of these new lab managerial changes is exogenous, it is possible that the entry of new lab managers coincides with other changes, potentially through their implementation of additional policies. While this is unlikely since pay was regulated by the Central Pay Commission, we nonetheless collated an exhaustive set of internal circulars and memoranda that outline the policy changes at CSIR labs from 1994 to 2004. Government rules required that CSIR labs publish each and every policy change as an official "circular." We collected 159 circulars over these years and found no confounding policies.[20]

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19. We do not observe the second managerial change in every case, so we impute the timing of the second managerial change based on the institutional rules governing the process, which we explained earlier. This represents an intention to treat. Moreover, based on our independent verification with each individual lab, these imputations are reliable. We nonetheless caution that the treatment effect here reflects an intent to treat status.

20. A related concern is based on a nationwide patent reform, which began in 1999. However, empirical evidence (perhaps surprisingly) suggests that these reforms tend to have either a minor (Sakakibara and Branstetter 2001) or potentially negative (Lerner 2002) impact on patenting. Even if it did have a positive effect, the new reforms would have simply made patenting more attractive for all entities, including CSIR. There is no

More formally, we examine how second-time lab managerial changes affect lab outcomes, controlling for the first-time change. For example, if the concern is that lab managerial entry is always associated with other unobserved organizational changes, then we should expect to see similar effects on patenting and licensing revenue following the *second* lab managerial entry. In contrast, if we find that all of the gains are concentrated in the first lab managerial change, then our results are consistent with the view that these labs had a lot of potential that could be capitalized upon with good management. However, as we reported in Section 4.2, second-time managerial changes do not predict any statistically significant positive (or negative) changes in innovation outcomes. To further address the concern that our null correlation is driven by a lack of power, we expand our sample to include 1990 to 2016, effectively doubling our sample size. We again find no evidence that second-time managerial changes are correlated with innovation outcomes (see Appendix B for details).

5.4 Other Miscellaneous Checks

As we discussed earlier in the empirical specification, we estimate the baseline specification again under two additional specifications: a quasi-maximum-likelihood conditional fixed effects Poisson model with standard errors clustered at the lab level and OLS with log(foreign patents filed + 1) and log(revenue_MNC + 1) and standard errors clustered at the lab level. The results, although omitted from the main text, remain qualitatively unchanged. We also used additional control variables, such as the number of Indian patents granted and filed by labs, the type of projects being pursued (based on internal circulars), and lab location. In every case, our estimates remain.

A final issue is whether the quality of scientific output declined following the rise in foreign patents. While we have already provided some evidence that quality continued improving using our scientist-level variation on publications, citations, collaborations, and sentiment, we provide additional evidence by collecting data on patent citations and the quality of journal publications from scientists in each lab. Table 4 shows that the number of patent citations and average journal impact factor grew steadily since 1997, which was approximately the time when new lab managers began entering these R&D labs. For example, average cumulative citations were roughly 13 with a standard deviation of 34.7 in 1997–1998, but they grew to 25.2 with a standard deviation of 64 by 2005–2006. Similarly, the journal impact factor index grew from 65.5 with a standard deviation of 102 in 1997–1998 to 164.8 with a standard deviation of 215.5

reason why it would interact systematically with the exogenous entry of new lab managers. We nonetheless compare the US patent grants of CSIR labs to US patent grants to other Indian public R&D labs and to Indian private firms. We find that CSIR labs outperform other Indian entities from 1994 to 2004.

Table 4. Time Series Evolution of Research Quality

	1997–8		1999–2000		2001–2		2003–4		2005–6	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Cumulative citations	13.7	34.7	15.8	40.8	21.0	55.4	22.8	60.0	25.2	64.0
Journal impact factor	65.5	102.0	72.6	106.4	80.0	130.2	110.2	165.1	164.8	215.5
Observations	35		36		36		36		36	

Notes: The table reports the (unweighted) average and standard deviation of cumulative citations among the patents developed by the scientists in each R&D lab and the average journal impact factor from the scientists' publication in the lab.
Source: CSIR, 1995–2006.

by 2005–2006. The growth in these quality measures cannot be explained by the marginal increases in federal funding.

We nonetheless recognize two possible limitations to the analysis. First, while research in the technology transfer literature suggests that there are many complementarities between patenting and university or lab research (Bozeman 2000; Kwanghui 2004), it is possible that publications could have increased even more if there was not a focus on commercializing revenue. Second, we cannot rule out an interpretation of our results that the entry of new lab managers simply unlocked several technologies that were being "stored up" in anticipation of the old generation lab managers' departure.[21] Since employees are generally aware of their lab manager's age and their tenure in the lab, they may anticipate the lab manager's exit. Even if this is true, however, it alters only the interpretation of our results—that the new generation of lab managers led to gains that represent the cumulative progress of multiple years. Indeed, much like the results from Atkin et al. (2017), where employees did not adopt the more cost-effective dye design for producing soccer balls, these results suggest that scientists were not as productive until new lab managers aligned with the CSIR aim entered the stage.

6. Conclusion

While there is now ample evidence that management practices are important determinants of firm productivity (Bloom and Van Reenen 2007; Bloom et al. 2013) and corporate strategy (Bertrand and Schoar 2003),

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21. Moreover, if we were simply detecting patents and discoveries that were stored up until after the manager changed, we should expect a negative effect after the second managerial change because of reversion to the mean. That is, if all of the new discoveries were stored up until the first managerial change, then subsequent discoveries would be lower, relative to trend, by the time the second managerial change took place. We do not see such a negative effect. The second managerial change is associated with a slight positive, but statistically insignificant, association with patenting and licensing revenues. We thank a referee for pointing out this insight.

there is little evidence about the specific mechanisms through which managers influence organizational outcomes and their interactions with other organizational features. Quantifying how managers communicate information (Komai et al. 2007), coordinate resources (Dessein et al. 2016), and interact with other design features in their organization (Ichniowski et al. 1997) is integral to understanding dispersion in productivity and corporate strategy.

We study a natural experiment throughout India's 42 public R&D labs following the appointment of a new national director to quantify how alignment between managers and financial incentives influences research and patenting productivity in organizations and among individual scientists. We find that the introduction of new scientists aligned with the new director's vision is associated with a significant increase in not only patenting and licensing to multinationals, but also publications, collaborations, citations, and morale among scientists. Our identifying variation exploits the staggered entry of new managers across locations and time, meaning that some scientists were exposed to new managers sooner than others. These effects are not driven by nonrandom sorting of better managers to better labs, nor by "Hawthorne effects" associated with other contemporaneous shocks to managerial entry.

Our paper raises several exciting areas for future research. First, while we demonstrated that new managers improved both resource allocation and morale among scientists, how do these two mechanisms potentially interact with one another for explaining good managers? Whereas some improvements in productivity might be realized simply by allocating resources more effectively, other improvements may take managerial vision and investments in the intangible capital of organizations. Second, are there general equilibrium effects? Whereas we identified improvements in research productivity among the labs and scientists in these labs, the surge in patenting and productivity was remarkable and likely attracted significant foreign investment and economic growth, suggesting that improvements in managerial quality might be especially important in certain sectors (e.g., education and R&D) where knowledge spillovers are large.

Conflict of interest statement. None declared.

Appendix A: Data Supplement

The CSIR has the responsibility of vision setting for the 42 national public R&D labs, comprising more than 12,500 scientific and technical staff employees. These public R&D labs in India are similar to those in other emerging markets, such as Embrapa and Fiocruz in Brazil and the CSIR labs in South Africa. As a point of comparison, these national R&D labs in India are almost twice as large as the Lawrence Livermore National Laboratory in the United States, which contains 6800 employees (as of

March 7, 2013) and has been the focus of study in prior literature (e.g., by Jaffe and Lerner 2001).

To construct the scientist-level data, we begin with the registry of scientists in the CSIR labs provided by their human resources department, granting us access to 595 unique authors. Authors are separated into first and last names. The first name contains either the initials or full name, depending on the format of the name in the file, together with the full last name. Using the RScopus author_data function, the author data were extracted from the Scopus API, providing an author identification code (scopus_id) and the scientist full name (author), as well as a list of their publications. Based on the acquired list of publications, we obtain the title of each article (produced by the scientist), the article identification numbers, keywords, the article type, and abstract. The information was aggregated into a large table with all articles for each scientist, but we restricted the sample to only those scientists who had published an article, producing a panel of 479 authors with a total of 51,579 articles.

Because Google Scholar provides a consistent way of tracking scientists over time, linked to each of their publications, we were able to compute an *h*-index for each scientist from their scopus_id. These data also provide information on scientists' skills and subject areas since each article is classified according to an expertise. However, because some of the author descriptions and abstracts were too short for us to use, we also draw on the PubMed database, which we searched using the entrez_fetch function in the entrez R library. Unfortunately, that approach did not produce any additional information, so we defer to the initial Scopus abstracts for our base.

To conduct our sentiment analysis, we parse text into vectors that are fed into a sentiment classifier that assigns a positive or negative sentiment score based on crowdsourced lexicons over eight primary emotions: anticipation, fear, joy, sadness, trust, disgust, surprise, and anger.[22] We restrict the sample to only words containing alphabet characters. We subsequently reduced these words into word lemmas, which reduces the inflections of a word to a single common root that can be compared with other words more easily. We subsequently fed this list of words into an NLP, specifically the syuzhet package in R (Jockers 2017), to produce a measure of sentiment. Each word is assigned a score, so we aggregate across words and abstracts to produce a sentiment index for each scientist over time. Not surprisingly, many words may not have a sentiment score. Out of our

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22. Each term in the lexicon corresponds with a given emotion. The package counts instances of the words assigned to each emotion by the lexicons at the sentence level through the get_nrc_sentiment function, creating an $N \times 8$ matrix where each column is one of the eight emotions, and each row is a sentence. The prop.table function converts these counts to proportions, allowing us to aggregate across sentences for each abstract. See: http://saifmohammad.com/WebPages/NRC-Emotion-Lexicon.htm.
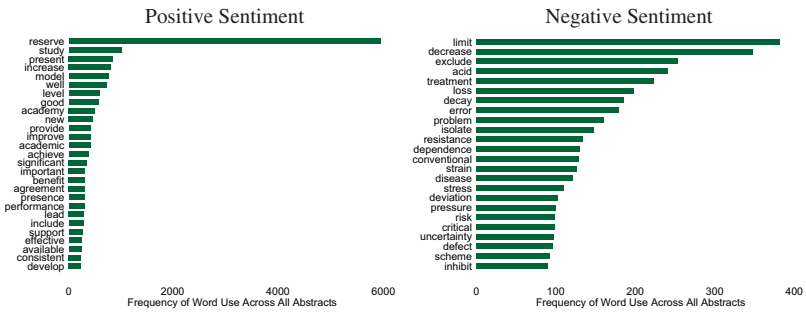
Figure A1. Examples of Positive and Negative Sentiment Words. The *y*-axis denotes the positive or negative sentiment word.
Notes: The figure plots the frequency distribution of positive and negative sentiment words obtained by feeding in each research abstract among scientists working in the CSIR public R&D labs from 1994 to 2006. These words are chosen based off of classification from the syuzhet package in R, which uses a lexicon of words classified by psychologists into categories of words that capture different emotions.

total articles, 44,975 articles had more than five words that could be classified by syuzhet sentiment analysis.

The lexicon is produced through crowdsourcing (obtaining high levels of responses on different words about the emotions they invoke), generating accuracy comparable or better than other approaches (e.g., surveying psychologists) (Mohammad and Turney 2012). While one concern is that these research abstracts do not contain meaningful variation in word choice to signal anything about scientists' sentiment or degree of interpersonal collaboration within the labs, it is ultimately an empirical question. As illustrative examples of the types of words that gain us identification, Figure A1 plots the most frequently used positive and negative sentiment words across all scientists in our sample of research abstracts. The most commonly used positive sentiment word is "reserve," whereas the most commonly used negative sentiment word is "limit."

In addition to the sentiment measure we constructed, we also gathered other information on scientists relating to their research productivity. While we considered measuring the average impact factor of the journal that scientists published in, gathering these data is much more time intensive because we would have to do so independently for each separate journal. Moreover, since many of these scientists are publishing in unranked journals, we would face a censoring problem. We have experimented, however, with a subset of journals for which we were able to gather impact factor data, and we obtain similar results. We believe that data on citations are more informative for gauging the research quality of scientific output since citation is a revealed preference measure of the applicability and/or quality of the output.
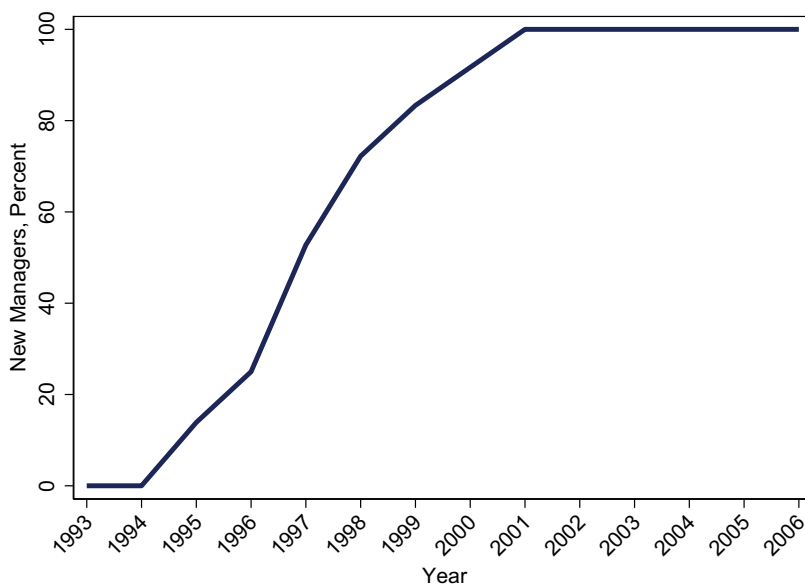
Figure A2. Timing of Entry Among New Generation Lab Managers.
Note: The figure plots the share of new managers in the R&D labs between 1993 and 2006.
Source: CSIR, 1993–2006.

A.1 Descriptive Statistics Supplement

When did the timing of new managers take place? Interestingly, it coincides almost exactly with the surge in patenting applications illustrated in the main text (Figure 1). Figure A2 plots the share of new generation managers in the lab, displaying the staggered entry since 1994. By 2000, all the old generation lab managers had been replaced. Of course, one concern with our motivating plot is that the rise in patenting applications is simply correlated with the managerial changes in CSIR labs. While our empirical strategy will address this concern in detail, we now provide evidence that CSIR labs account for the overwhelmingly majority of the increase in patents, particularly those abroad from the United States during these years. To examine this quantitatively, we gather data on all patenting activity throughout India and examine what accounts for the overall increase in the 1990s and 2000s.

Table A1 summarizes a series of panel regressions comparing US patenting at CSIR with similar patenting at other public R&D labs and universities in India (Columns 1 and 2), private firms in India (Columns 3 and 4), and state-owned firms in India (Columns 5 and 6). We used both fixed effects models (Columns 1, 3, and 5) and random effects difference in difference models (Columns 2, 4, and 6). We regress logged US patenting on an indicator for whether the origin of the patent is a CSIR lab and its interaction with an indicator for post-1996 since the bulk of the patenting took place following the early 1990s after Dr. Mashelkar entered.

Table A1. Comparing US Patenting of CSIR Labs to Other Indian Entities

Independent variable	Sample: CSIR labs, all other public R&D labs and public universities		Sample: CSIR labs and all private Indian firms		Sample: CSIR labs and all state owned firms	
	(1) ln (US patents)	(2) ln (US patents)	(3) ln (US patents)	(4) ln (US patents)	(5) ln (US patents)	(6) ln (US patents)
1[CSIR lab]	–	1.75** (0.81)	–	1.75** (1.02)	–	1.71** (0.87)
1[$t > 1996$] × [CSIR lab]	1.84*** (0.02)	1.84** (0.89)	1.83*** (0.02)	1.83*** (0.89)	1.73*** (0.10)	1.73** (0.82)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	533	533	2041	2041	117	117
Model	Fixed effects	Random effects	Fixed effects	Random effects	Fixed effects	Random effects

Notes: The table reports results of regressions that compare US patents at CSIR labs to other Indian entities. Models 1 and 2 compare CSIR labs to other Indian public R&D labs and universities; models 3 and 4 compare CSIR labs to Indian private firms; models 5 and 6 compare CSIR labs to Indian state-owned enterprises. The analysis is done for baseline year 1996 (first full year of Mashelkar's tenure as Director General of CSIR). Similar results not reported here are obtained for dummy year 1999 (midpoint of Mashelkar's regime). Models 1, 3, and 5 are fixed effects, and models 2, 4, and 6 are random effects/difference in difference models. For each patent, we code the variable "ownership," and we code 1640 US patents (1994–2005). Heteroskedasticity-robust consistent standard errors are reported within parentheses.
*** denotes 1%, ** denotes 5%, and * denotes 10% significance.
Source: CSIR, 1995–2006.

Regardless of our sample and whether we use random or fixed effects specifications, patenting in CSIR labs disproportionately increased US patenting, relative to other public R&D labs in India, rather than other state-owned firms in India and Indian private firms.

While the "new generation of lab managers" entering labs directed resources toward IP commercialization, the "old generation of lab managers" fundamentally disagreed with the aim of licensing with multinationals and wanted to remain dependent on government support.[23,24] We proceed by further examining differences between old and new

23. For example, new lab managers, such as J.S. Yadav and K.V. Raghavan at IICT Hyderabad, directed resources toward several projects aimed at supporting IP commercialization. Some of these projects included supporting a new Biotechnology Incubation Center (BTIC), setting up a Centre for Analysis of Chemical Toxins (CACT), setting up a Pre-Biotechnology Incubation Centre (PBIC), and investing in data mining and data warehousing for IP commercialization. A very concrete example of this new generation of leaders was Ehrlich Desa, the director at the National Institute of Oceanography (NIO), who publicly stated: "My task now is to lead NIO in the current environment, where we have to do first-rate oceanography while earning revenue." "*Fish curry, feni, and oceanography*" *Business India, November 30–December 13, 1998*.

24. Krishna (2007) provides an exhaustive account of the growth in CSIR laboratories and elucidates a major issue facing the labs in the 1980s. Quoting Ward Morehouse's (1978: 374) case study of a CSIR laboratory, Krishna (2007) remarks that "one of the major limitations affecting industrial research in India has been the lack of work after the laboratory

Table A2. Comparison of Observed Differences Among New and Old Lab Managers

	N	Age	Patents	Number of countries visited	Number of awards	Publications
New lab managers (post-1994)	52	49.3	8.8	7.3	1.8	112.0
Old lab managers (pre-1994)	9	52.3	7.3	3.7	1.0	66.0
t-Statistic of difference		2.03**	0.57	5.45***	0.66	8.02***

Notes: The table reports the means across several observed characteristics over new and old lab managers. The information on these lab managers is hand collected through CVs sourced through CSIR and web-based searches for additional information.
*** denotes 1%, ** denotes 5%, and * denotes 10% significance.
Source: CSIR, 1995–2006.

generation managers across the different labs. Our point is not that these managers are identical, but rather that they differ in their alignment with the "CEO vision"—that is, Dr. Mashelkar's vision for research in these labs. Table A2 documents several interesting differences across scientists. New generation managers tend to be slightly younger (49.3 versus 52.3 years old), publish more (112 versus 66 publications), and have more international experience (7.3 versus 3.7 countries visited).[25] These differences reflect the alignment between their set of experiences and the agenda that Dr. Mashelkar wanted to accomplish during his tenure as director of CSIR.

Is India unique in its institutional setting? Based on experiments conducted to date, our setting is stereotypical of many developing countries. For example, Atkin et al. (2017) document similar organizational barriers to adoption of more cost-effective dyes among soccer ball producers in Pakistan due to an agency conflict between employees and lab managers. Similarly, Banerjee et al. (2012) find that leaders in the Rajasthan, India, police force need help in implementing recommended management interventions properly to experience the full benefits. Bloom et al. (2013) find that the introduction of lean manufacturing practices among Indian textile producers is associated with significant and sustained productivity gains. Karplus and Zhang (2017) find that the introduction of energy efficiency practices is associated with improvements in energy management and energy cost reductions, but sustained adoption of the energy management practices is heavily dependent on lab managerial interest. Lemos and Scur (2017) also reaffirm these insights using a management

stage, which is essential if laboratory know-how is to be translated into commercially usable form."

25. The fact that new managers have a lot more international travel experience is also consistent with Giorcelli (2019), who provides causal evidence that visits and training in the United States among Italian managers led to a rise in productivity and technology transfer following their return to Italy.

survey tool for India, Mexico, and Colombia. More broadly, Hsieh and Klenow (2009) have documented the presence of large misallocation across developing countries, such as India and China, in comparison to the United States.

Appendix B: Main Empirical Results Supplement

Figure A3 plots the coefficients associated with estimating Equation (1) when the outcome is logged foreign patent filings. We find that foreign patents filed by a lab increase in the years following the arrival of a new lab manager. In particular, patent filing is 28% higher (p-value = 0.091) in the first year following the lab managerial change and 37% higher (p-value = 0.032) in the fourth year following the change, relative to the baseline when the new lab manager enters the lab. These estimates are also invariant to the inclusion of government budgetary support for labs as a control. Importantly, there is no pre-trend: The 2 years prior to the lab managerial change exactly offset to zero and have p-values of 0.200 and 0.645.

Why do we observe an initial spike in patent filings followed by a slight decline and a subsequent rise? Although the coefficients on the $t + 1$, $t + 2$, $t + 3$, $t + 4$, and $t + 5$ dummies are all statistically indistinguishable from one another because of the small sample size, we explored the large initial jump through interviews with personnel in these labs. One scientist we interviewed stated, for example, that the appointment of new leaders "immediately unlocked the stock of existing possible patents sitting on the bench." In this sense, scientists may have been stockpiling some of their ideas in anticipation of the incumbent lab manager's exit. If so, our estimated coefficients best represent a cumulative effect of lab managerial entry on patenting activity, relative to a 2- or 3-year baseline, rather than the $t = 0$ year the new lab manager entered.

We subsequently explore the effects of lab managerial entry when our outcome variable is logged revenue from multinationals. These coefficients are displayed in Figure A4. We again find no evidence of a pre-trend in the 2 years prior to lab managerial entry, with coefficients that effectively sum to zero and have p-values of 0.797 and 0.253. However, starting the second year after new lab managerial entry, we begin to find an increase in revenue of 28.5%, although it is imprecisely estimated (p-value = 0.338).[26] We subsequently find that revenue has increased by 55.9% (p-value = 0.057) in the third year following the lab managerial change and by 54.9% (p-value = 0.082) the fourth year after the change. Consistent with the R&D process, licensing revenue does not immediately

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26. We learned from our interviews that most licensing deals were accounted for as a "stock deal" where, in most cases, the revenue is capitalized and recognized in the year of signing the licensing deal.
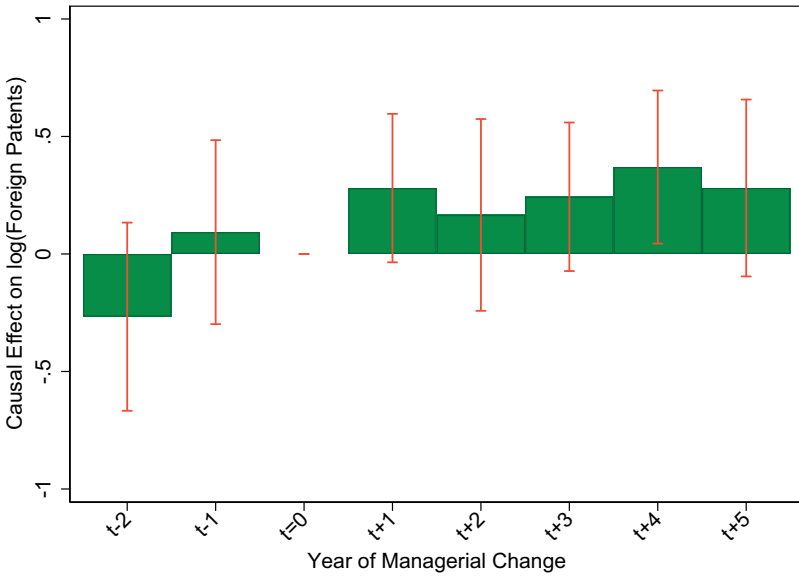
Figure A3. Effects of Lab Managerial Entry on Foreign Patenting.
Notes: The figure plots the coefficients associated with regressions of logged foreign patent filings on indicators for years before and after the entry of new lab managers into the 36 public R&D labs, controlling for lab- and year-fixed effects and logged government and industry budgetary support. Standard errors are clustered at the lab level.
Source: CSIR, 1995–2006.

flow in following patent filings. It is, therefore, comforting that we observe some of a lag, at least relative to the patent filing results from Figure A3.

While these results point toward quantitatively significant causal effects of managerial entry on innovation outcomes, one potential concern is that managerial changes are correlated with an array of other unobserved organizational changes that drive differences in innovation outcomes. To examine the possibility that managerial changes take place with other changes, we exploit variation in second-time managerial changes through regressions of the form:

$$y_{ilt} = \gamma^1 \text{FIRST\_MGMT}_{lt} + \gamma^2 \text{SECOND\_MGMT}_{lt} + \beta X_{it} + \phi_{i,l} + \lambda_t + \epsilon_{it},$$

where we now distinguish between the first and second managerial changes, focusing on the coefficient estimate of γ^2. To address the concern that our earlier exercise in the main text is underpowered, we expand the sample to 1990 to 2016, focusing on scientist-level research outcomes, which are made available through Google Scholar over an extended period. Because we have 26 years of variation, with many second managerial changes happening in the mid-2000s, we have enough power to detect an effect if one exists.
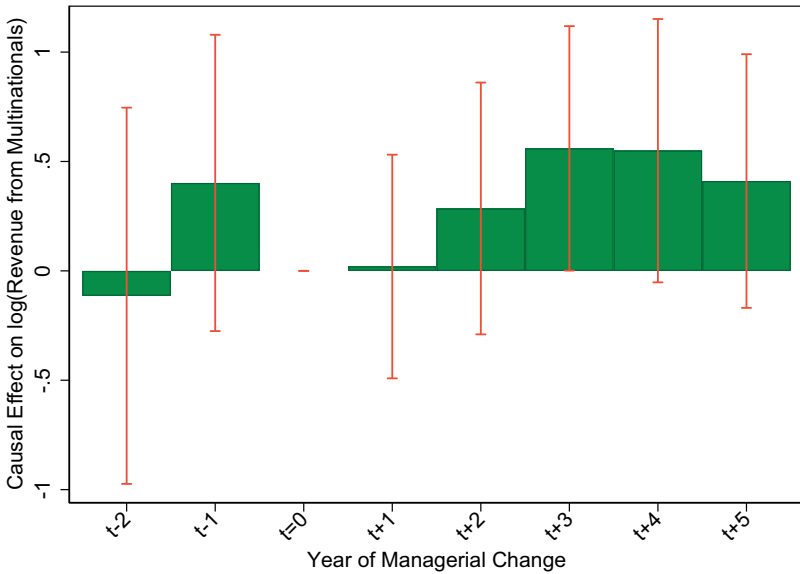
Figure A4. Effects of Lab Managerial Entry on Multinational Revenue.
Notes: The figure plots the coefficients associated with regressions of logged revenue from multinationals on indicators for years before and after the entry of new lab managers into the 36 public R&D labs, controlling for lab- and year-fixed effects and logged government and industry budgetary support. Standard errors are clustered at the lab-level.
Source: CSIR, 1995–2006.

Table A3 documents these results. Although our direct effects of γ^1 are now less statistically precise than in our baseline (as we have included the second-time change and we do not include our usual controls since they are not available for these latter years), we see that the coefficients on the second-time managerial changes are all incredibly imprecise and not even in the right direction much of the time. For example, second-time managerial changes are associated with very imprecise declines in the scientist *h*-index, number of articles, and number of citations. We, therefore, conclude that our causal effect of the first managerial change is representative of the genuine impact of CEO and managerial alignment on innovation outcomes.

We now provide some concluding evidence about the quality of publications over time, in particular highlighting that the rise of patenting did not trade off with either the quantity or quality of publication. Adopting a measure of research quality using citation-weighted publications, as in Azoulay et al. (2007) who use it to characterize the "fundamental pursuit of knowledge," Figure A5 shows that there is an overwhelming increase in publication quality starting primarily in 2000 where we see that the trend increase in quality is statistically different from zero. Our specification

Table A3. Robustness Examining the Effects of First versus Second Managerial Changes on Scientist Outcomes, 1990–2016

Dep. var.=	log (Sentiment) (1)	log (H-index $t+2$) (2)	log (Number of articles $t+2$) (3)	log (Number of coauthors $t+2$) (4)	log (Number of citations $t+2$) (5)	log (Number of techniques) (6)
1[1st managerial change]	0.061	0.066	0.088	0.098*	0.119	0.134**
	[0.037]	[0.098]	[0.081]	[0.055]	[0.184]	[0.056]
1[2nd managerial change]	0.002	−0.060	−0.068	−0.053	−0.153	0.029
	[0.050]	[0.074]	[0.042]	[0.050]	[0.116]	[0.047]
R-squared	0.33	0.60	0.55	0.46	0.54	0.45
Sample size	9249	9423	9423	9423	9423	9423
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Person FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table reports the coefficients associated with regressions of different scientist outcomes on an indicator for whether the first lab managerial change has taken place, conditional on year- and person-fixed effects. We focus on six different outcomes: (1) sentiment in period t, which is generated by feeding in all the words in scientists' abstracts into the R package syuzhet, (2) H-index in period $t+2$ (measure of a scientist's publication impact), (3) logged number of research articles produced in period $t+2$, (4) logged number of coauthors in period $t+2$, (5) logged number of citations for articles published in period $t+2$, and (6) logged number of new techniques used in the research in period t. For a discussion of the construction of outcomes (1) and (6), see the main text. Standard errors are clustered at the lab level, and no weights are used.
***- denotes 1%, ** denotes 5%, and * denotes 10% significance.
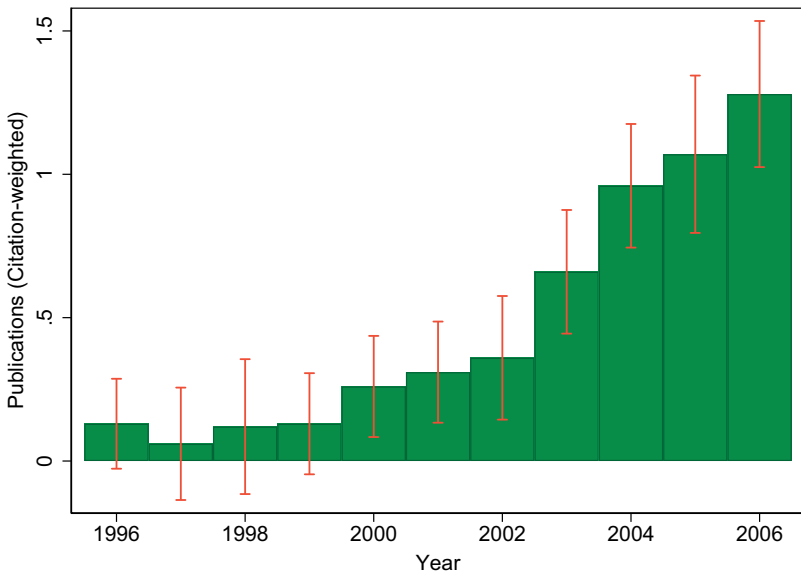*Source:* CSIR, 1990–2016.

Figure A5. Citation Weighted Publications, 1996–2006.
Notes: The figure reports the coefficients associated with regressions of citation-weighted publications on year-fixed effects, normalized to 1995 as the baseline. The outcome variable is the log of citation-weighted publications produced using the number of publications and impact factor of them (using Thomson indices). Fixed effects on labs are also included, but results are robust to their exclusion, too. Standard errors are clustered at the lab level.
Source: CSIR, 1996–2006.

plots the coefficients on year-fixed effects when the outcome variable is logged citation-weighted publications, controlling also for lab-fixed effects.

Appendix C: Qualitative Evidence from a Case Study

While we have provided causal evidence that new managers led to an increase in lab and scientist outcomes, we now go through a case study (based on interviews with Dr. Mashelkar and other CSIR executives) that analyzes the impact that these successes in foreign patenting had on attracting new business and investment from large international companies, like GE. When Dr. Mashelkar took over in 1989 as Director of the NCL, one of the CSIR labs, he significantly altered the lab's output. Prior to his arrival, CSIR filed for less than five foreign patents every year. Upon his entry, however, NCL scientists were asked to prioritize research in the area of polymer preparation, condensation, and polycarbonates. They eventually filed for the first US patents in this area.

Table A4. Diffusion of Practices Through Imitation of NCL–IICT Model

Dep. var.=	log (Patent mix)		log (Patents filed abroad)
	(1)	(2)	(3)
Joint projects with NCL	0.024***	0.023***	0.105**
	[0.008]	[0.008]	[0.042]
×1[t>Managerial change]		0.015*	
		[0.008]	
R-squared			
Sample size	310	310	394
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Notes: The table reports the coefficients associated with regressions of the logged patent mix and logged patents filed abroad on the number of joint projects between NCL and IICT and its interaction with an indicator for after the managerial change, conditional on controls, which include: logged government funding, the fraction of individuals in the lab with a PhD, the average countries visited, the share who have visited foreign countries, number of research papers, books, processes, articles, reports, awards, and year-fixed effects normalized to 1995. Standard errors are clustered at the lab level.
*** denotes 1%, ** denotes 5%, and * denotes 10% significance.
Source: CSIR, 1995–2006.

Around 1991, NCL started interacting with GE, the firm being a large purchaser of THPE,[27] and Hoechst Celanese USA, which was the only supplier of THPE to the global market. In 1994, NCL initiated a program funded by GE aimed at developing a proprietary process for THPE. In parallel, NCL started aggressively patenting in the USPTO system and filed several US patents in the area of polymers from 1994 to 2000.[28] In interviews, Dr. Mashelkar and other NCL scientists stressed the role played by the first few USPTO patents on polymers in "getting a foot in the door at GE." The GE-NCL alliance worked successfully for nine years and was successful in breaking the global monopoly of Hoechst in the area of THPE. NCL earned revenues of around \$8.5 million from GE over these years.

Can we quantitatively test this hypothesis? We examine the diffusion of managerial practices by examining how joint cooperation with the NCL lab ("patent mix") behaved after a new manager enters a lab, controlling for other factors. Table A4 presents these results using random effects regressions. For example, we see that an additional increase in NCL-IICT joint project is associated with a statistically significant 2.4% increase in patent mix. These effects are not simply driven by an aggregate increase in patenting or R&D given that we include time-fixed effects. Moreover, as we see in Column 2, these effects are largely driven by the entry of a new manager, who is associated with a 1.5% increase in the

27. 1,1′,1″-Tris(4′-hydroxyphenyl) ethane; a branching agent used in the synthesis of high grade polycarbonates.
28. For example, US patents 5,780,578, 5,851,546, 6,379,599, 6,420,487, 6,605,714, 6,689,836, 6,794,467, and 6,867,268.

patent mix. Turning away from patent mix, Column 3 shows that these joint NCL-IICT projects are also associated with a significant 10.5% increase in patents filed abroad. Put together, these results provide causal evidence that adoption of best practices from the NCL-IICT model was associated with a rise in research productivity across other labs.

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