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Abstract

This paper exploits a natural experiment in the entry of new lab managers across India's 42 public R&D labs between 1995 and 2006 to study the complementarity between lab managers and incentive schemes. While scientists were provided with stronger incentives to patent and license from multinational companies in 1994, the "old generation" of lab managers disagreed with these aims and failed to adequately support scientists' efforts. First, we show that the introduction of new lab managers aligned with the national R&D reforms is associated with a 58% rise in patenting and 75% rise in licensing revenues from multinationals. Second, using additional information on each scientist in these labs, we examine how their research productivity changed in response to different managers. Notably, we find that the entry of new lab managers is associated with improved research productivity: 15.6% higher h-indices, 11.7% more coauthors, 12.7% more research articles, and 25.1% more citations per scientist. Moreover, using natural language processing (NLP) techniques on the set of research abstracts produced among these scientists, we find that overall mood and sentiment

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increased by 9.4% following the first managerial change. Our results highlight the important complementarities between incentives and management practices, especially in developing countries. A back-of-the-envelope calculation that suggests India could save on 9-24% of its R&D and related subsidy expenditures under the entry of new generation lab managers.

JEL: L22, L23, O32, O33

Keywords: incentives, innovation, management, productivity, research and development.

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 lab 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 effects of managers on organization and individual -level outcomes, focusing on the complementarity between management and incentives.

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 for at least two reasons: (i) better managers are matched to better firms that vary in other unobserved ways (Gayle et al., 2015), and (ii) due to the presence of complementarities, identifying exogenous variation that affects one organizational feature (e.g., managers), but not another, is rare (Athey and Stern, 1998).

To overcome these empirical challenges, we exploit variation arising from the unique institutional features of India's 42 public research and development (R&D) labs comprising over 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% shared among all employees of the lab.[1]

Despite the significant strengthening of incentives, we show that the "old generation" of lab managers did not respond by raising inventive activity. Through a series of 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 a "lab 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, 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 between 1994 and 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 six-year employment contract or after they reached the retirement age of 60 (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 15.6%, 12.7%, 11.7%, and 25.1% increase in scientists' *h*-index,

[1]Source: CSIR letter 9/203/94-TU, June 15, 1994.

number of articles, number of coauthors, and number of citations, respectively. Moreover, we feed each scientists' research abstract into a natural language processing (NLP) algorithm to produce a sentiment index of scientist morale in labs, finding a 9.4% 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 causal evidence that management practices have a positive, causal, and persistent effects on firm productivity (Bloom et al., 2013, 2017b) and employee engagement (Makridis, 2018; Hoffman and Tadelis, 2017), 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 only have a positive effect on organizational outcomes when paired with other practices. For example, almost analogously to Atkin et al. (2017) who highlight how resistance among employees 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. In this sense, while transitions towards greater performance pay might have positive effects productivity in settings with sufficiently robust capital markets and management practices (Lazear, 2000; Paarsch and Shearer, 2000; Bandiera et al., 2005; Makridis, 2017), they can be completely ineffective in settings with weak management practices and/or non-compliant lab managers. Our results also highlight the importance of proper execution of management practices through the selection of managers.

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. In our setting, while scientists were given stronger incentives to patent following the incentive reform, lab managers in the R&D labs ultimately had the real authority to govern the effective incentives for the scientists. Managers play an especially important role in leading by example to cultivate trust (Hermalin, 1998). By building trust over a series of 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).

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., 2017a), 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 is an important determinant of corporate culture.

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).[2]

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

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

"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).

However, managers do not make decisions in isolation—they interact with a broader web of organizational characteristics and 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, 2017). Our paper shows that important complementarities can emerge between incentives and management, much like the complementarity across human resource practices introduced by Ichniowski et al. (1997). The lack of managerial oversight to allocate and authorize resources can undermine otherwise strong incentives and hold organizations back from their potential. Appendix Section A formalizes these insights by illustrating within the lens of a principal-agent model that agents (e.g., lab managers) with tastes for domestic over foreign output will produce a suboptimal amount of aggregate research for the principal.

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 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, coining the phrase "patent, publish and prosper" based on his view that "patents are wealth creators."[3] One of the reasons that Dr. Mashelkar was particularly suited for the new responsibility was that he had great success in securing U.S. patents on polymers and licensing these patents to multinationals, like General Electric, while serving in a CSIR lab based in Pune (National Chemical Laboratory [NCL]). During those years, Dr. Mashelkar traveled to the U.S. to foster engagements with General Electric. 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 all 41 other labs would not be easy. For example, salaries of scientists 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 centrally determined 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 of complementarities since one of the primary identification challenges in empirical work is that the introduction of new management leads to other organizational changes (Athey and Stern, 1998); here, these other changes are shut down.

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. As we discussed earlier, incumbent lab managers could be replaced only if they ended their six-year contract term or retired by reaching age 60. These bureaucratic rules were enforced in every case. Since these incumbent scientists joined without knowledge of Dr. Mashelkar's rise to director of the CSIR,

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

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.

3.1.2. New Incentives to Compensate Scientists

India's national labs traditionally had a policy of sharing licensing revenue with individual inventors until the 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% to be shared among all employees of the lab in question, and 5% 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 towards 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 towards projects that had a higher likelihood 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 towards 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 B1.).

[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 track every lab managerial change at these labs between 1994 and 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 and one lab ceased to exist.

In fact, Dr. Mashelkar 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".[8] 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, therefore, 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 comes from all 42 national R&D labs that are part of the Council of Scientific and Industrial Research (CSIR), containing information on patent filings and patent grants, revenue from multinationals, government budgetary support, and lab characteristics and location all between 1994 and 2006 during Dr. Mashelkar's tenure as director. We also collected the CVs from 61 lab managers across 36 labs and the CVs from over 500 senior scientists, as well as gathering each scientist's Google Scholar profile Our field-work 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 that there was little quality control and, therefore, 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 only applicable to indigenous Indian agriculture. To motivate the significance of managerial entry, Figure 1 plots the number of patent applications between 1960 and 2016. Remarkably, patenting applications are nearly flat between 1960 and 1990, before surging in 1994, which coincided with the entry of new managers. For example, between 1990 and 2010, patenting applications among non-residents (residents) grew by 1,056% (672%).

[INSERT FIGURE 1 HERE]

Table 1 documents several descriptive statistics in the baseline dataset more formally. Revenue

[8] http://www.outlookindia.com/printarticle.aspx?233803. Website accessed on February 24. 2012

from multinationals grew dramatically between 1994 and 2006 over a factor of four. Meanwhile, funding from the government in these labs changed only marginally. Importantly, patents granted grew in not only India, but also, and much more so, in the U.S. and abroad. For example, patents granted by the U.S. 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 average share of scientists with a PhD was 79% in 1994-2000 and 2001-2006. Put together, we see little change, if any, in the composition of actual scientists in these labs.[9]

[INSERT TABLE 1 HERE]

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:

$$y_{ilt} = \gamma MGMT_{lt} + \beta X_{it} + \phi_{i,l} + \lambda_t + \epsilon_{it} \tag{1}$$

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 are 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 vary over time across labs, namely patent filings and licensing revenue. If, for example, new lab managers aligned with Dr. Mashelkar's vision of patenting and licensed enter the labs, we should observe an increase in their research activity and licensing to multinationals. Our second set of outcomes vary 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

[9] Appendix Section B1. 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 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.

(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. Mashelkar's new vision were approved to head the labs.

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 non-random matching could happen in one of two ways. First, scientists could strategically sort into better labs. Second, Dr. Mashelkar could select particularly high performing managers and assign them to particularly high performing labs to create momentum. We examine both these possibilities below.

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 financial compensation Stern (2004). We nonetheless provide a quantitative test of our intuition by correlating 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. While our matched sample only consists of eight observations, the correlation is 0.04.

Second, we collect the CVs among 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 for eleven cases stayed the same, suggesting that unobserved differences in lab managerial affinity with Dr. Mashelkar cannot account for these effects.

If the entry of new lab managers is not confounded by non-random sorting, how can we interpret γ as the causal effect of alignment between the CEO and managers on innovation outcomes? Importantly, Dr. Mashelkar selected managers based on their alignment with the new CSIR vision on commercialization of patents and publication in scientific journals. However, these managers were not selected on the basis of managerial ability or political ties to Dr. Mashelkar.

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.[10] Not surprisingly, failing to control for time-invariant differences across labs produces upwards 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

[10]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).

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 Section C also 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 grow over time.

4.3. Scientist-level Results

We now turn towards 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 a natural language processing (NLP) algorithm whereby words are parsed into positive or negative emotions, which we aggregate into an annual sentiment index for each scientist (see Appendix Section B for further detail and examples of qualifying words). 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 proxy for the resources available for research.[11] Although both measures are imperfect, they serve as novel proxies for morale and creativity among scientists within labs over time.

Table 3 now 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

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

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 20.3% following the entry of a new lab manager and scientists' h-index rises by 28.3%.

Turning to our fixed effects estimator in our even-numbered columns, we find that lab managerial entry is associated with a 9.4% rise in scientific sentiment and a 5.4% increase in the number of new techniques used in conducting research, although the latter is not statistically significant at conventional levels. We also find widespread evidence that research productivity along traditional margins increases. For example, lab managerial entry is associated with a 15.6% increase in scientists' h-index, 12.7% increase in scientists' publication of new articles, 11.7% increase in the number of coauthors among scientists, and 25.1% increase in the number of citations. Even though the variation in the timing of managerial entry is quasi-random, it is still possible that upwards 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 that might explain systematically better performance for one lab over another.

[INSERT TABLE 3 HERE]

4.4. Robustness Exercises

We implement a wide array of robustness exercises in Appendix Section D. First, we show that our estimated treatment effects do not reflect a "Hawthorne effect" whereby employee morale rises after any organizational change. Second, we provide further evidence that the timing of managerial changes is not correlated with real outcomes of scientific productivity within the labs. Third, we provide further evidence that other potential unobserved factors are not correlated with these managerial changes. Fourth, we provide further evidence that these improvements in licensing revenue and patenting did not trade off with basic research and/or quality.

5. Aggregate Effects

Our microeconomic evidence relates closely with a macroeconomic literature about the impact of misallocation on aggregate productivity (Restuccia and Rogerson, 2008). For example, Hsieh and Klenow (2009) estimate an equilibrium model with plant-level micro-data and find that equalization of marginal products between capital and labor would raise productivity by 40-60% in India's manufacturing sector. We, therefore, conduct a simple back-of-the-envelope test to examine the aggregate implications for R&D in India. Our goal is not to provide a reliable quantitative estimate for policy making, but rather a heuristic that highlights the importance of complementarity between incentives and management practices, especially in developing countries.

We start with the assumption that all R&D in India is subject to the same misallocation that was present in the national R&D labs prior to Dr. Mashelkar's entry into the position of director for CSIR. Total R&D expenditures in India are roughly \$9.5 billion and subsidies for R&D and related activities are roughly \$5 billion.[12] Since we do not observe R&D expenditures, but we do observe patenting activity, we treat the latter as a proxy for the underlying R&D process. We now assume that replacing all of the old generation lab managers in India with new generation lab managers would deliver comparable gains as the ones we obtained here, focusing specifically on licensing revenue. Given our elasticity of 0.58 for foreign patenting, and under the assumption that a 1% rise in R&D is associated with a 0.056-0.143% rise in GDP (Blanco et al., 2016), then our estimates imply that replacing the bad lab managers would lead to between a 3.25% (0.58×0.056) and 8.29% (0.58×0.143) rise in Indian GDP, or \$390-995 million in 2006, simply by replacing old generation lab managers who are failing to provide the proper authorization for funding and scientific inquiry.[13] While the scale of misallocation might seem small, the estimate amounts to 9.37-23.92% of India's overall subsidies to these R&D activities per year and represents a lower bound since we are simplifying from the spillover effects of better management on organizational productivity and of more R&D on knowledge production.

[12]To compute the R&D expenditures, we first obtained R&D expenditures as a share of GDP for India, which is 0.79% in 2006 according to the World Bank data. We also found that India's GDP (in current USD) was \$1,201,111,768,409, meaning that R&D expenditures in 2006 were \$9,488,782,970 or nearly \$9.5 billion. To compute the subsidy expenditures, we take an estimate of the 2017 budget on government spending on subsidies and focus on the category of payments going to miscellaneous categories, i.e., non agriculture, petroleum, or interest, which amounts to roughly 12% of 2,72,276 crore (or 12% of \$41 billion). https://www.businesstoday.in/union-budget-2017-18/decoding-the-budget/budget-2017-subsidies-rise-by-5-per-cent/story/245647.html

[13]An alternative approach would be to use our elasticity between management and licensing revenues and assume that the licensing revenue increase would be re-invested in R&D. However, since we could not find information on aggregate revenues coming from licensing, we could not complete the aggregation exercise.

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), 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 non-random sorting of better managers to better labs, nor by "Hawthorne effects" associated with other contemporaneous shocks to managerial entry. Our estimated elasticities suggest that replacing lower quality managers could save 9-24% of India's overall budget for R&D subsidies annually.

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, while we provide a back-of-the-envelope calculation of the aggregate effects for these improvements in managerial quality, 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.

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7. Tables and Figures

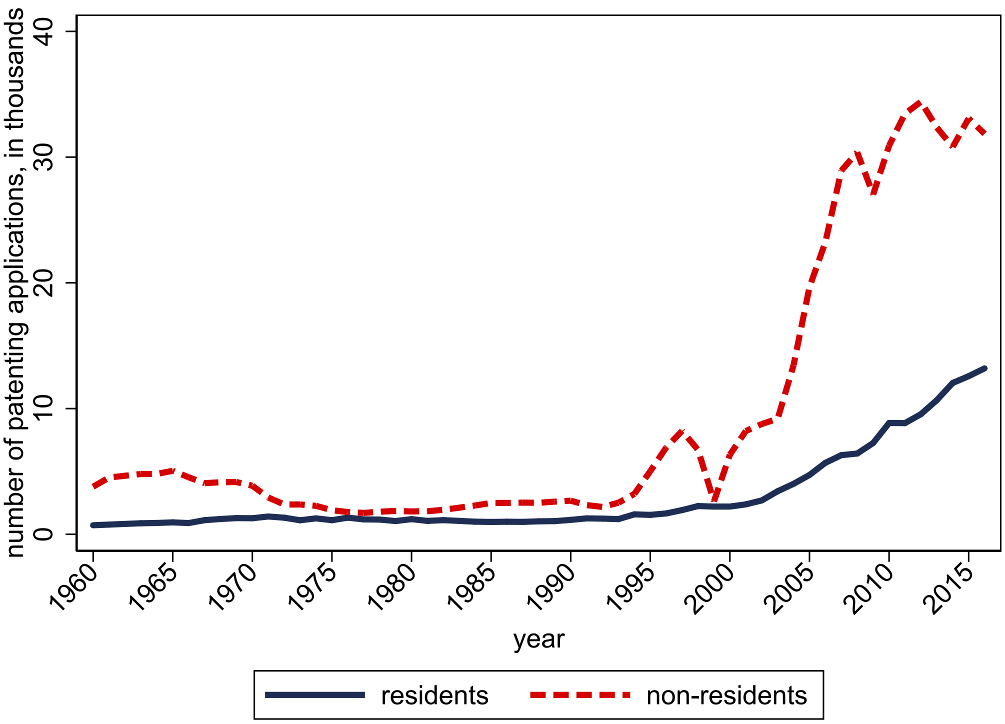

Figure 1: Patenting Applications Among Residents & Non-Residents, 1960-2016

Notes.—Sources: World Intellectual Property Organization (WIPO), WIPO Patent Report: Statistics on Worldwide Patent Activity. The figure plots the number of patenting applications from residents and non-residents. 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.

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, US	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 sci assoc, pct	0.12	0.25	0.12	0.25	0.12	0.25
scientists with phd, pct	0.79	0.18	0.79	0.18	0.79	0.18
scientists visit to US, pct	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.–Sources: CSIR, 1994-2006. 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 refer to more detailed characteristics about the scientists. All nominal variables are in Rs. crore where crore represents $10 million.

Table 2: The Effects of Managerial Changes on Lab Outcomes, 1994-2006

Dep. var. =	ln(patents filed abroad t+1)		ln(licensing revenue t+2)	
	(1)	(2)	(3)	(4)
1[post management change]	1.13***	.58*	1.41***	.75**
	[.25]	[.29]	[.32]	[.33]
R-squared	.16	.73	.22	.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.–Sources: Council of Scientific and Industrial Research, 1994-2006. 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.

Table 3: The Effects of Managerial Changes on Scientists, 1994-2006

Dep. var. =	ln(sentiment)		ln(h-index t+2)		ln(# articles t+2)		ln(# coauthors t+2)		ln(# citations t+2)		ln(# techniques)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
1[post management change]	.203***	.094**	.283**	.156**	.157***	.127**	.193***	.117**	.474***	.251*	.123***	.054
	[.040]	[.044]	[.106]	[.074]	[.055]	[.059]	[.050]	[.047]	[.159]	[.136]	[.038]	[.038]
R-squared	.02	.40	.01	.70	.01	.69	.01	.55	.01	.66	.01	.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.–Sources: CSIR, 1994-2006. 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: (i) sentiment in period t, which is generated by feeding in all the words in scientists' abstracts into the R package `syuzhet`, (ii) h-index in period $t+2$ (measure of a scientist's publication impact), (iii) logged number of research articles produced in period $t+2$, (iv) logged number of coauthors in period $t+2$, (v) logged number of citations for articles published in period $t+2$, and (vi) logged number of new techniques used in the research in period t. For discussion of the construction of outcomes (i) and (vi), see the main text. Standard errors are clustered at the lab-level and no weights are used.

A Motivating Theoretical Model

While our main text outlines the conceptual case for the complementarity between managerial quality and financial incentives, we now provide a more formal characterization. We draw on the simple framework in Bolton and Dewatripont (2005) with the following setting in mind. Consider a principal-agent problem where the CEO (Dr. Mashelkar) is the principal and the lab manager is the agent. Suppose that lab managers can produce either domestic or foreign output, each with their own payoffs. However, now suppose that lab managers have their own taste for different types of output—for example, one lab manager might prefer producing domestic output over foreign output, manifesting in the fact that the lab manager may not want to license patents to multinationals and pursue projects that are internationally competitive. It follows that the lab manager with these unobserved tastes for domestic output will produce a sub-optimal amount for the principal, requiring greater financial incentives to achieve the same level of overall output.

We now formalize these ideas. Suppose that lab managers can produce two types of output (domestic and foreign), given by:

$$q_i = e_i + \varepsilon_i, \quad i \in \{D, F\}$$

where e denotes the amount of effort that the lab manager invests and $\varepsilon \sim \mathcal{N}(0, \sigma^2)$. Effort for a lab manager could involve, for example, monitoring scientists, approving projects, and working to cultivate a culture of innovation and inquiry. Suppose that lab managers have preferences over compensation, denoted w, effort, and potentially domestic output, denoted η:

$$u_D(w, e) = -\exp[-\iota(w - \psi(e_D + e_F) + \eta_D)]$$

$$u_F(w, e) = -\exp[-\iota(w - \psi(e_D + e_F))]$$

where ι denotes the elasticity of intertemporal substitution, w denotes the equilibrium wage, $\psi(e)$ is a function of effort, and η_i captures the potential preference that a lab manager might have for producing domestic output. Suppose that the principal and agent are restricted to a set of linear contracts:

$$w_i = t + sq_i$$

where t denotes the base wage and s denotes the variable component of pay. The principal solves the following problem:

$$\max_{e,t,s} E(q_i - w_i)$$

subject to individual rationality and incentive compatibility constraints

$$E[u_i(w,e)] \geq u(\overline{w})$$

$$e \in \arg\max E[u_i(w,e)]$$

To the extent that the principal only cares about profits (i.e., net research output), then lab managers who have an additional preference for domestic output will generate a sub-optimally high production of domestic output at the expense of foreign output.

B Data Supplement

The Council of Scientific and Industrial Research (CSIR) has the responsibility of vision-setting for the 42 national public R&D labs individual labs, comprising of over 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 number of employees in the Lawrence Livermore National Laboratory in the United States, which contains 6,800 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 was extracted from the Scopus API, providing an author identification code (scopus_id), 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 we previously did not have, 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 crowd-sourced lexicons over eight primary emotions: anticipation, fear, joy, sadness, trust, disgust, and anger.[14] We restrict the sample to only words containing alphabet characters. We subsequently reduced these words into word lemmas, which reduce the inflections of a word to a single common root that can be compared with other words more easily. We subsequently fed these 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 total articles, 44,975 articles had more than 5 words that could be classified by `syuzhet` sentiment analysis.

The lexicon is produced through crowd-sourcing—obtaining high levels of responses on different words about the emotions they invoke—generating accuracy comparable or better than other

[14]We use 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.

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 2 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".

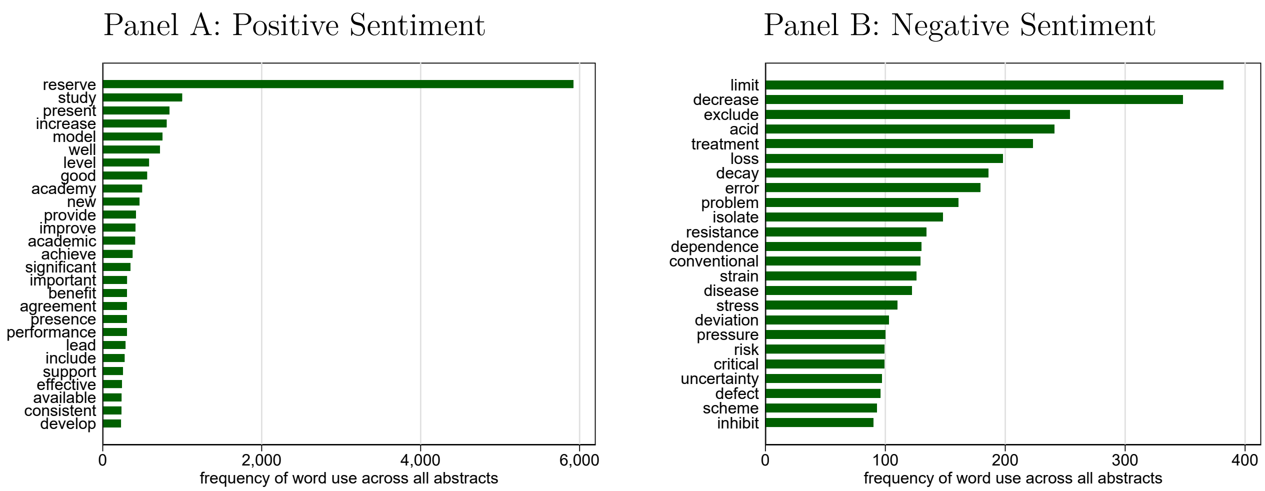

Figure 2: Examples of Positive and Negative Sentiment Words

Notes.–Sources: Google Scholar. 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 between 1994 and 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.

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 we were able to gather impact factor data over and obtain similar results. We believe that data on citations is more informative for gauging the research quality of scientific output since citation are a revealed preference measure of the applicability and/or quality of the output.

B1. 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 3 plots the share of new generation managers in the lab, displaying the staggered entry since 1994. By 2000, all the 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 U.S. 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.

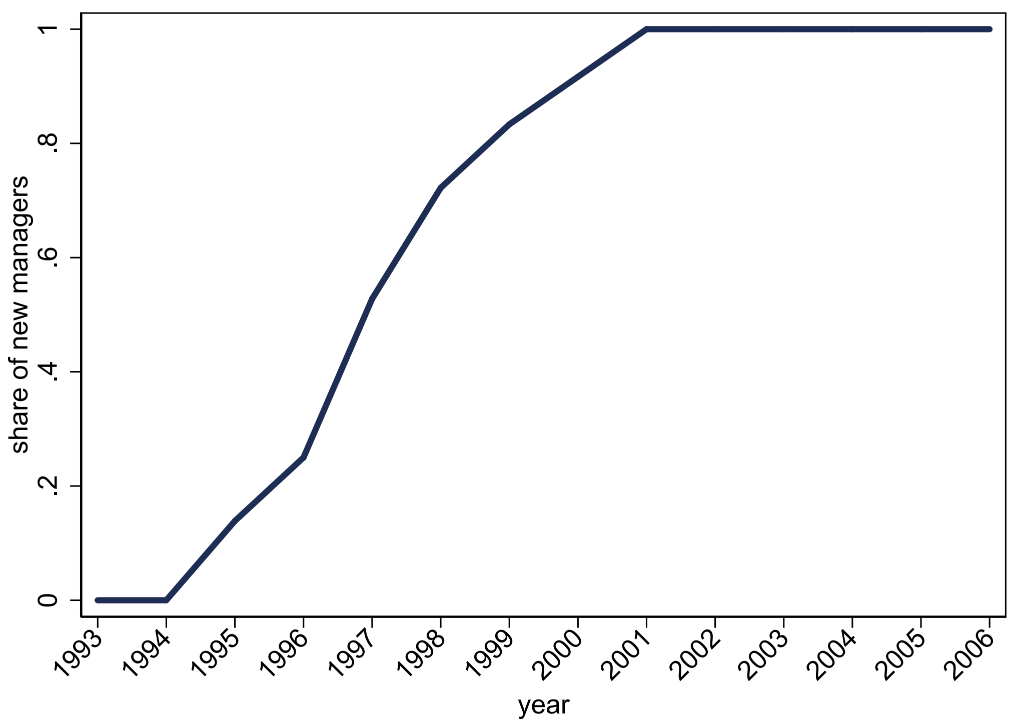

Figure 3: Timing of Entry Among New Generation Lab Managers
Notes.–Sources: CSIR, 1993-2006. The figure plots the share of new managers in the R&D labs between 1993 and 2006.

Table 4 summarizes a series of panel regressions comparing U.S. patenting at CSIR with similar patenting at other public R&D labs and universities in India (columns I and II), private firms in India (columns III and IV), and state-owned firms in India (columns V and VI). We used both fixed effects models (columns I, III and V) and random effects difference in difference models (columns II, IV, VI). We regress logged U.S. 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. Regardless of our sample and whether we use random or fixed effects specifications, patenting in CSIR labs disproportionately increased U.S. patenting, relative to other public R&D labs in India, rather than other state-owned firms in India and Indian private firms.

	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	
	Dependent Variable					
	(1)	(2)	(3)	(4)	(5)	(6)
Independent Variable	*ln(US patents)*	*ln(US patents)*	*ln(US patents)*	*ln(US patents)*	*ln(US patents)*	*ln(US patents)*
1[CSIR Lab]	-	1.75** (0.81)	-	1.75* (1.02)	-	1.71** (0.87)
$1[t > 1996]\times1$[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

Table 4: Comparing U.S. Patenting of CSIR Labs to Other Indian Entities

Notes.–Sources: CSIR, 1995-2006. The table reports results of regressions that compare U.S. patents at CSIR labs to other Indian entities. Models I and II compare CSIR labs to other Indian public R&D labs and universities; models III & IV compare CSIR labs to Indian private firms; models V & VI compare CSIR labs to Indian state-owned enterprise. The analysis is done for baseline year 1996 (first full year of Mashelkar's tenure as Director General CSIR). Similar results, not reported here are obtained for dummy year 1999 (mid point of Mashelkar's regime). Models I, III and V are fixed effects and models II, IV and VI are random effects/difference in difference models. For each patent, we code the variable 'ownership' and we code 1640 U.S. patents (1994-2005). Standard errors are heteroskedasticity-robust.

While the "new generation of lab managers" entering labs directed resources towards 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.[15],[16] We

[15]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' published in the Business India, issue of November 30-December 13, 1998.*

[16]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, p. 374) case study of a CSIR laboratory, Krishna

proceed by further examining differences between old and new 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 5 documents several interesting differences across scientists. New generation managers tend to be slightly younger (49.3 versus 42.3 years old), publish more (112 versus 66 publications), and have more of an international experience (7.3 versus 3.7 countries visited). 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.

	N	Age	Patents	# Countries Visited	# 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***

Table 5: Comparison of Observed Differences Among New and Old lab managers

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

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 are 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 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.

(2007) remarks that "one of the major limitations affecting industrial research in India has been the lack of work after the laboratory stage, which is essential if laboratory know-how is to be translated into commercially usable form."

C Main Empirical Results Supplement

Figure 4 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 two 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 slightly decline and additional 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 two or three year baseline, rather than the $t = 0$ year the new lab manager entered.

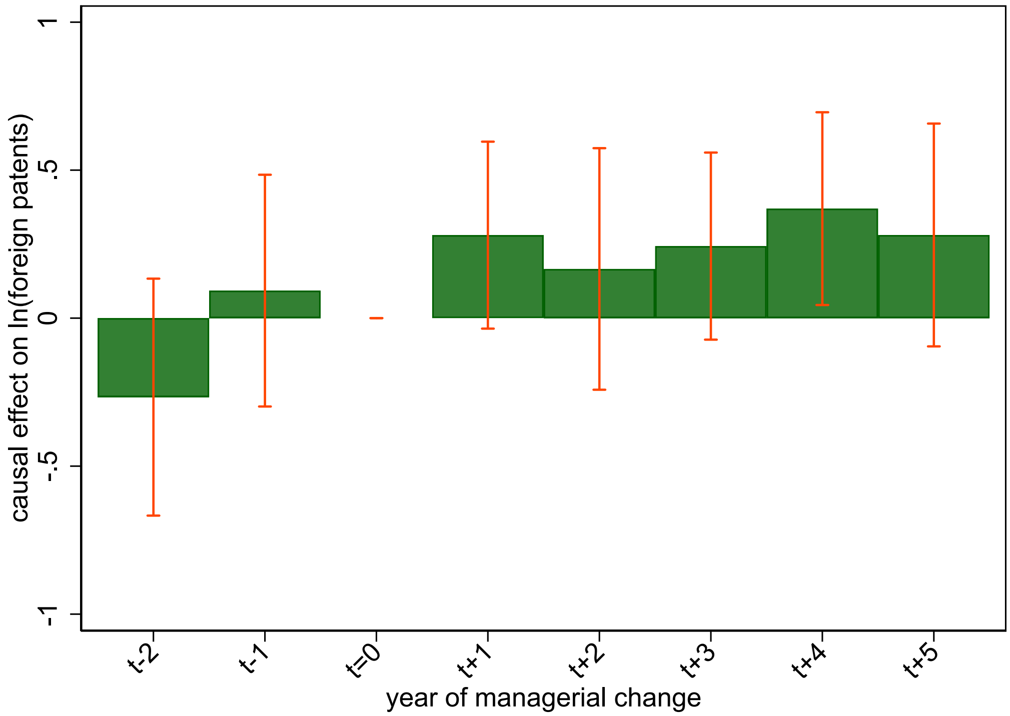

Figure 4: Effects of lab managerial Entry on Foreign Patenting

Notes.–Sources: Council of Scientific and Industrial Research, 1995-2006. 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.

We subsequently explore the effects of lab managerial entry when our outcome variable is logged revenue from multinationals. These coefficients are displayed in Figure 5. We again find no evidence of a pre-trend in the two 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).[17] We subsequently find that revenue has increased by 55.9% (p-value = 0.057) in the third year following the lab managerial change and an increase of 54.9% (p-value = 0.082) the fourth year after the change. Consistent with the R&D process, licensing revenue does not immediately 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 4.

[17] 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.

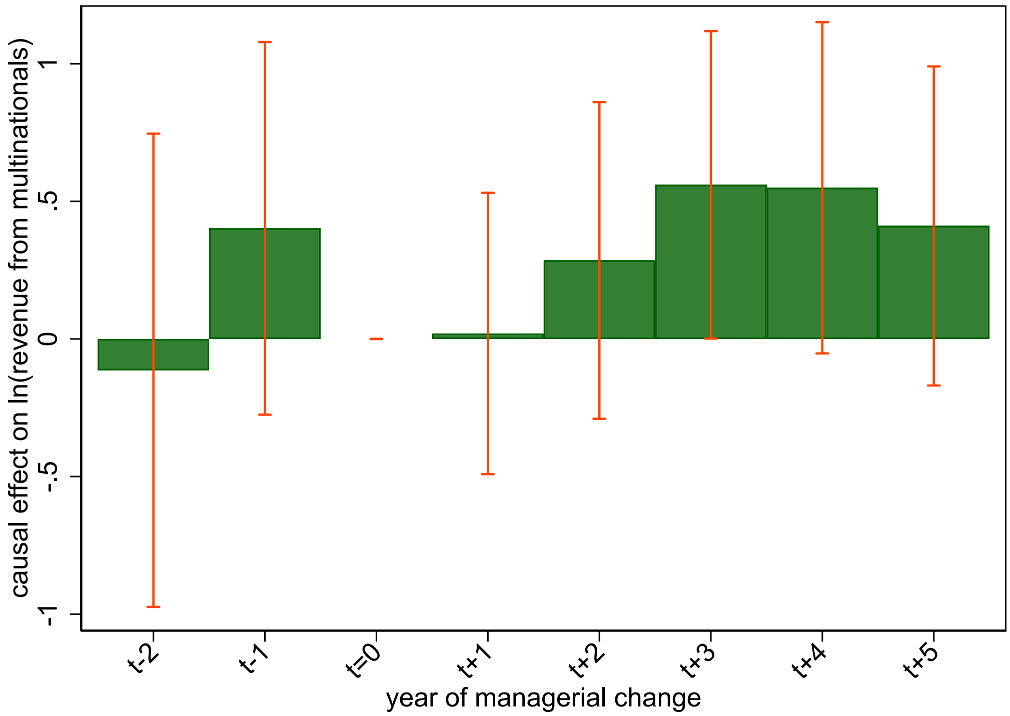

Figure 5: Effects of lab managerial Entry on Multinational Revenue

Notes.–Sources: Council of Scientific and Industrial Research, 1995-2006. 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.

While these results point towards 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:

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

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 under powered, we expand the sample to 1990 and 2016, focusing on scientist-level research outcomes, which are made available through Google Scholar over an extended period. Because we have 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

Table 6 documents these results. Although our direct effects of γ^1 are now less statistically precise as 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.

D Additional Robustness Exercises Supplement

D1. 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 leverage the fact that some labs exhibit more than one managerial change over our sample horizon. Regressing logged sentiment on an indicator for the first and second managerial 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). 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, therefore, conclude that our causal effect of managerial entry on scientific productivity is coming from changes introduced by the first new generation lab manager.

D2. Timing of Managerial Changes

We turn towards 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, 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. 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

Table 6: Robustness Examining the Effects of First versus Second Managerial Changes on Scientist Outcomes, 1990-2016

Dep. var. =	ln(sentiment)	ln(h-index t+2)	ln(# articles t+2)	ln(# coauthors t+2)	ln(# citations t+2)	ln(# techniques)
	(1)	(2)	(3)	(4)	(5)	(6)
1[1st managerial change]	.061	.066	.088	.098*	.119	.134**
	[.037]	[.098]	[.081]	[.055]	[.184]	[.056]
1[2nd managerial change]	.002	-.060	-.068	-.053	-.153	.029
	[.050]	[.074]	[.042]	[.050]	[.116]	[.047]
R-squared	.33	.60	.55	.46	.54	.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.–Sources: CSIR, 1990-2016. 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: (i) sentiment in period t, which is generated by feeding in all the words in scientists' abstracts into the R package `syuzhet`, (ii) h-index in period $t+2$ (measure of a scientist's publication impact), (iii) logged number of research articles produced in period $t+2$, (iv) logged number of coauthors in period $t+2$, (v) logged number of citations for articles published in period $t+2$, and (vi) logged number of new techniques used in the research in period t. For discussion of the construction of outcomes (i) and (vi), see the main text. Standard errors are clustered at the lab-level and no weights are used.

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.

D3. 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 between 1994 and 2004. Government rules required that CSIR labs publish each and every policy change as an official "circular". We collected 159 circulars over these and found no confounding policies.[18]

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 report 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 Section C for details).

[18]A related concern is based on a nation-wide 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 reason why it would interact systematically with the exogenous entry of new lab managers. We nonetheless compare the U.S. patent grants of CSIR labs to U.S. patent grants to other Indian public R&D labs and to Indian private firms. We find that CSIR labs outperform other Indian entities between 1994 and 2004.

D4. Other Miscellaneous Checks

Like 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 7 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 into these R&D labs. For example, average cumulative citations was 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 2005-6. Similarly, the journal impact factor index grew from 65.5 with a standard deviation of 102 in 1997-8, but it grew to 164.8 with a standard deviation of 215.5 by 2005-6. The growth in these quality measures cannot be explained by the marginal increases in federal funding.

Table 7: 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.–Sources: CSIR, 1995-2006. 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.

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. Since employees are generally aware of their lab manager's age and how long he has been in the lab, they may anticipate the lab manager's exit. Even if this is true, however, it only alters 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.