Process Standards and Management Practices: Evidence from Peru

David Alfaro-Serrano*

Columbia University

November 14, 2019

Job Market Paper

Most updated version here

Abstract

This paper explores the role of adoption costs as a determinant of managerial upgrading and proposes a feasible way to promote the adoption of better management practices by firms. Using a regression discontinuity strategy, I show that a subsidy to certify process standards, such as ISO 9001, increases certification probability and, additionally, induces the adoption of modern management practices that are beyond the standards' scope. Managerial improvement is concentrated in monitoring and target-setting practices, while no change is detected in practices related to incentives for employees. These findings are consistent with a model in which process documentation, which is required by the standards, and modern management practices are complementary and suggest that subsidizing the certification of process standards is a feasible way to improve management.

*E-mail: da2628@columbia.edu I would like to thank professors Eric Verhoogen, Jonas Hjort, and Réka Juhász for their advice and support; professors Michael Best, Donald Davis, Christian Pop-Eleches, Amit Khandelwal, Suresh Naidu, David Weinstein, and Jack Willis for their valuable comments; Alejandro Afuso, Celia Cornejo, Rafael Castillo, Luis Mesías, Juan Manuel García, Santiago Cueto, and Eduardo Zegarra for their help during this project; Andrea Quijano and Johnathon F. Cherry for their research assistance; and Nuria Alfaro Serrano for her help with the model figures. I am also indebted to the *Grupo de Análisis para el Desarrollo* (GRADE) for providing a productive and stimulating work environment during my stay in Peru; and to *Innóvate Perú* for providing information needed for this project. This research would not have been possible without the financial support provided by Columbia University's Department of Economics development colloquium and Program of Economic Research, the Center for Development Economics and Policy (CDEP), and the National Science Foundation (NSF). All views, opinions, and conclusions expressed are my own.

1 Introduction

Several studies suggest that the use of modern management practices, such as monitoring internal processes, setting explicit targets, and incentivizing employees, is important for firm growth and therefore the economic progress of developing countries (Bloom and Van Reenen (2010), Syverson (2011), Bloom et al. (2013), Bloom et al. (2019)). However, many firms, especially those in developing countries, do not adopt such practices (Bloom et al. (2013), McKenzie and Woodruff (2017), Giorcelli (2019)). Studies seeking to understand this lack of managerial upgrading have mainly focused on the role of informational limitations (Bloom et al. (2013), McKenzie and Woodruff (2014), Cai and Szeidl (2017), Bloom et al. (2018), Bloom et al. (2019)). At the same time, studies have paid limited attention to the role of adoption costs, even though such costs play an important role in the analysis of the adoption of other technologies.

Understanding the impediments to managerial upgrading is important because such knowledge sheds light on the barriers to firm growth and it may help us explain the large variation in management practices and productivity that has been observed across firms (Syverson (2004), Hsieh and Klenow (2009), Bloom and Van Reenen (2007), Bloom and Van Reenen (2010), McKenzie and Woodruff (2017)). Additionally, a good understanding of the reasons behind the lack of managerial upgrading is important for policy design. If informational limitations are the main obstacle to upgrading, actions to promote it should focus on facilitating training and the flow of information about management techniques. If adoption costs also play a relevant role, these initiatives could be complemented with subsidies, a type of intervention that governments have experience dealing with. In fact, papers assessing the effectiveness of policy-feasible interventions that address informational constraints have found mixed results (Bruhn and Zia (2013), Karlan and Valdivia (2011), Giné and Mansuri (2014), Drexler et al. (2014), Valdivia (2015), Karlan et al. (2015), Cai and Szeidl (2017), Higuchi et al. (2019)) while a recent paper by Bruhn et al. (2018) suggests that subsidies might be a helpful policy tool.

An often underappreciated aspect of the cost of adoption of modern management practices is that they rely on the availability of data about processes within the firm, and gathering that data is in itself a difficult task. One of the determinants of this cost is whether firms have documented processes. Documenting firm processes entails explicitly deciding how they will be carried out, designing them in a way that allows the recovery of records about their execution, and writing them down. Once processes have been documented, collecting data about them becomes easier. In this sense, there is complementarity between process documentation and the modern management practices.

This paper tests this idea of complementarity and suggests using it to design a policy-feasible way to promote the adoption of modern management practices. I do this by studying whether a subsidy for the certification of widely known process standards, such as ISO 9001, induces the adoption of modern management practices beyond their scope. In what I call the *certification program*, Peruvian firms received a government subsidy to adopt and certify process standards. This required standardizing and documenting the internal processes of the firm but did not require the adoption of specific practices or the achievement of specific goals. However, as mentioned above, it may be that these standards facilitate the adoption of better management practices by reducing their adoption cost. In other words, in the presence of complementarity between the standards and sound management practices, subsidizing the adoption of the former should also induce the adoption of the latter.

The study of the complementarity between process documentation and management practices is difficult due to identification and data challenges. The identification challenge is that, in general, firms that acquire process standards are different from those that do not in aspects that might also be relevant for the adoption of modern management practices. I address this issue with the use of a regression discontinuity design in a real policy setting, exploiting the subsidy assignment mechanism. To apply for the subsidies, firms had to submit a project, which was reviewed and given a score. Only those with a score above a certain threshold were funded. In the neighborhood of the threshold, the subsidy can arguable be considered as good as randomly assigned. In addition to the identification challenge, the fact that data about management practices are rarely available also complicates the analysis. To solve this issue, I ran a survey to collect information about management practices in the last quarter of 2018, three years after treatment assignment, and built a management index. Like the index in Bloom and Van Reenen (2010), this index measures the adoption of practices related to monitoring, target-setting, and provision of incentives to employees.

This paper has five main findings. First, the certification program accomplished its stated goal of promoting the certification of process standards. The intervention triggered an increase of 65% in the certification probability. Second, more importantly, the program induced the adoption of modern management practices beyond the scope of the certification. The management index, which runs between zero and one, increased by 0.13. This value is equivalent to 33% of the index mean, 0.56 times its standard deviation, and 35% of the difference between the 25th and 75th percentiles. This finding is consistent with a model in which the process documentation required by the standards and the modern management practices measured by the index exhibit complementarity. Third, managerial upgrading is explained by improvements in monitoring and target-setting practices, while no change is detected in the use of incentives for employees. Fourth, firms that receive the subsidy also show evidence of an increase in the likelihood of improvements in machinery and infrastructure, consistent with the previous evidence showing that the adoption of modern management practices is associated with firm growth. Fifth, the study also finds a large positive, although statistically nonsignificant, increase in productivity measured as sales per worker. The magnitude of this change is similar to other estimates in the literature.

This paper relates to several strands of literature. The most direct link is with the literature on management practices. In this regard, the contribution is twofold. First, this paper presents evidence consistent with the idea that adoption costs are a relevant barrier to the adoption of better management practices. This complements previous studies that have focused on the role of informational limitations in an effort to understand the lack of managerial upgrading. Second, this paper also suggests a policy-feasible intervention to help reduce those adoption costs: subsidizing the certification of widely popular process standards, which in turn promotes the adoption of better management practices due to their complementarity. From an implementation perspective, this type of intervention has several advantages compared with others that have been studied. First, given that the standards are already codified, the implementing agency does not have to create curricula of knowledge to be transmitted nor choose a set of practices to be promoted. Second, the existence of a market of support services for the adoption of popular process standards means that the implementing agency can limit itself to providing funding and letting the beneficiary firms hire help if they need it. Third, a subsidy for the certification of process standards is simple to monitor because the certification is an easily verifiable signal of project completion. Fourth, the cost is within what a government or development agency can afford. On average, firms treated by the certification program received USD 11,000, which is similar to the cost of other government interventions promoting managerial improvement[1] and lower than the cost of the intensive interventions studied, for instance, by Bloom et al. (2013) and Giorcelli (2019).[2]

This paper also relates to the literature on process standards. While this field has seen few papers in economics (Volpe Martincus et al. (2010), Masakure et al. (2009), Sun and Ouyang (2014), Bernini et al. (2017), Calza et al. (2019)), there is a larger body of work among management scholars (Sampaio et al. (2009), Tarí et al. (2012), Heras-Saizarbitoria and Boiral (2013), Boiral et al. (2018), Heras-Saizarbitoria et al. (2019), Riaz et al. (2019)). Understanding the changes that these standards trigger within firms is one of the main questions in the field. In this paper, I present quasi-experimental evidence of the impact of adopting process standards on the internal practices of companies.

More broadly, this paper also contributes to the literature on technology adoption. The lack of technology upgrading is a pervasive development problem, and low levels of firm capacity have been advanced as one of the possible causes (Bustos (2011), Goñi and Maloney (2017), Cirera and Maloney (2017)). This paper presents evidence consistent with this view, as the presence or absence of complementary technologies can be thought of as a component of firm capacity.

The rest of the paper proceeds as follows. Section 2 reviews the literature on process standards, management practices, and firm performance. To guide analysis, section 3 presents a model that illustrates the idea of complementarity between process standards and modern management practices, and describes how policy can exploit this relationship to foster managerial improvement. Section 4 describes the empirical strategy, and section 5 presents the results. Finally, section 6 concludes.

2 Literature review

2.1 Management and productivity

The management practices used by a company are one of the determinants of the way in which inputs are transformed into outputs; hence, they are part of technology of the firm[3]. Although it is conceivable that some management techniques are convenient or not dependent on context, some studies have shown that certain management practices are associated with higher firm growth in different sectors and countries. Bloom and Van Reenen (2007) and

[1]For example, the Mexican program studied by Bruhn et al. (2018) had a cost of USD 10,670 per firm treated with largest subsidy option.

[2]The consulting intervention in Bloom et al. (2013) had an approximate market value of USD 250,000 per treated firm, while the intervention studied by Giorcelli (2019) had a cost of USD 38,723 (without considering the fact that its viability relied on the backing provided by the U.S. government).

[3]Foster and Rosenzweig (2010) define technology as “the relationship between inputs and outputs” (p.396). Bloom et al. (2016) explicitly argue that management can be treated as a technology.

Bloom and Van Reenen (2010) have shown that monitoring what occurs within the firm, setting explicit targets, and providing incentives to employees are practices associated with higher performance. Similar results have been found by McKenzie and Woodruff (2017) in a study focusing on the monitoring and target-setting practices of small firms in developing countries.

Some experimental and quasi-experimental studies have suggested that at least part of the relationship between management practices and performance is causal. Bloom et al. (2013) and Bloom et al. (2018) analyze an experiment in which they assigned Indian textile firms to receive management consultancy services from a top U.S. consultancy company. They find that the intervention led to an increase in the adoption of recommended management practices a few months into the treatment, and produced and increase in productivity (TFP) of 16.6% after one of year of treatment, although this figure is noisily estimated. Based on these results, the authors impute an annual increase of approximately USD 325,000 in annual profits, which they estimate to represent, on average, a doubling of profitability. Giorcelli (2019) performed a quasi-experimental analysis of the effect of a U.S. assistance program to improve management on a set of Italian firms. She finds that the program induced the adoption of sound practices, such as performing regular maintenance on machinery or recruiting managers who were not kin. Importantly, this study shows that the effects of the intervention unfolded over a long period of time. Beneficiary firms increased their productivity (TFP) by 15.1% one year after the beginning of the 3-year intervention, and this number reached 49% after 15 years. These findings raise an obvious question: why did the firms not adopt these practices on their own? Bloom et al. (2013) collected data suggesting that informational barriers, in the form of ignoring the existence of the practices or their profitability, were the main obstacles. Giorcelli (2019) also suggests that this type of barrier plays an important role in explaining why the nontreated firms in her setting did not adopt better management practices even when it was apparent that treated firms had improved their performance. In a different study, Bloom et al. (2019) also present evidence suggesting that lack of information plays an important role in explaining why U.S. firms do not upgrade their management. Moreover, Bloom et al. (2018) and Bloom et al. (2019), also provide evidence suggesting that the use of modern management practices is associated with the mobility of managerial personnel who are knowledgeable about such practices, reinforcing the idea that information availability is an important determinant of managerial upgrading.

While the studies by Bloom et al. (2013) and Giorcelli (2019) suggest that management is important and that firms do not improve it on their own, they do not provide a clear path to creating policies to promote upgrading. In both cases, the interventions cannot just be replicated given their cost and complexity. The consultancy intervention in Bloom et al. (2013) was provided by a top U.S. consultancy firm, had a market cost of USD 250,000 per treated company, and included a one-month diagnostic phase followed by four months of support to implement the recommendations. This support phase was quite intense, as it involved approximately 15 days of consultant time per month-plant and had the explicit goal of helping to implement and stabilize the new practices. The quasi-experimental study by Giorcelli (2019) considered an actually implemented policy, but it was also an abnormally intense one. Managers of treated firms traveled to visit U.S. plants for eight to twelve weeks to learn about their management practices. These trips were followed by a 3-year monitoring period in which U.S. experts visited the treated plants, observed the state of the implementation and provided advice. The explicit cost of the program was USD 38,723 per treated firm. Although this is substantial, it underestimates the complexity of the intervention. The U.S. government had to not only cover the program's explicit cost but also convince U.S. companies to spend time and effort to gratuitously transfer part of their know-how to Italian firms. Clearly, this coordination effort was possible only due to the geopolitical interests at stake.

Given the relevance of management and the idea that lack of information is one of the main obstacles to its improvement, different papers have analyzed policy-feasible ways to help overcome this barrier. These studies have found mixed results, as summarized by McKenzie and Woodruff (2014). Among others, Karlan and Valdivia (2011), Bruhn and Zia (2013), and Drexler et al. (2014) study the impact of in-class business training programs. Karlan and Valdivia (2011) find that adding business training to a standard microcredit program improves knowledge about sound business practices and induces the adoption of some of them, such as keeping records of bank withdrawal, but not of other important ones, such as keeping records of payments to workers. The authors also find no effects on performance. Bruhn and Zia (2013) find that the beneficiaries of a training program increased their business knowledge and declared with higher probability that that they introduced new production processes. Although the authors did not codify the content of the new processes, they indicate that adopting systematic stock management was part of them. Increases in profits were only detected among female-run firms. Drexler et al. (2014) explore in more detail how different teaching techniques alter the effects of training interventions. They compare the traditional approach, which is based on transmitting comprehensive business knowledge in class, with a novel approach based on rules-of-thumbs. Their finding is that the rules-of-thumbs approach induces changes in management practices, while the traditional approach does not. Consistently, the rules-of-thumbs treatment increased an index of revenue measures while the traditional treatment failed to achieve this.

Instead of pure in-class training, Karlan et al. (2015), Valdivia (2015), and Higuchi et al. (2019) explored the effectiveness of on-site consultancy components. Karlan et al. (2015) find that management consultancy administered to tailoring microenterprises in Ghana led to a temporary improvement in management practices, but they reverted back to normal after the first year. Additionally, there were no effects on profitability. Valdivia (2015) randomly allocated Peruvian businesswomen to receive in-class training, or a combination of training and on-site technical assistance. He finds that only a few of the suggested practices were actually adopted and that they depended on the type of treatment received. Regarding performance, the study also finds that both treatment arms led to a 15% increase in sales. However, the link between this improvement and the treatment is hard to establish because the level of take-up and the completion rate were low. Higuchi et al. (2019) randomly allocated a sample of Tanzanian firms to receive in-class training, on-site consultancy, or a combination of both. The content of the classes and consultancy included the standard modules on marketing and accounting and basic modules of Kaizen. The authors find that the three treatment arms induced changes in management practices one year after treatment, that the combined treatment induced increases in sales and value-added two years after treatment and that the on-site consultancy treatment induced noisily estimated increases in these variables three years after treatment.

In a variation of the previously described consultancy interventions, Bruhn et al. (2018)

study the effect of a subsidy that covered between 70% and 90% of the cost of hiring local consultants in Puebla (Mexico). The content of the service was jointly decided by them and the business-owners, and the consultants worked with the firms for one year. The authors find a 26% increase in productivity (TFP) immediately after treatment, although this figure is imprecisely estimated and was not concurrent with an increase in performance. However, within five years after treatment, the authors find that average employment and total wage bill were higher among treated firms.

2.2 Process standards

Using process standards to promote the adoption of better management practices is a promising but still unexplored possibility, as the nature and popularity of these standards makes information about them accessible and allows the existence of experienced consultancy firms that provide support.

Process standards[4] are guidelines to systematize and document the internal processes of the firm. Given that their aim is to be universally applicable, they do not prescribe specific practices or goals. Instead, they require the processes to be standardized, written down, and designed to leave a record (Heras-Saizarbitoria and Boiral (2013), Braun (2005)). Adopting a process standard is challenging and usually involves hiring experienced consultants to help with the task. Firms can certify compliance with these standards. If they decide to follow that path, they need to be audited by a "registrar", which is a company authorized to certify compliance with a given process standard. This audit includes a review of the required documentation, a review of the process records, and on-site visits and interviews with employees. Different process standards refer to different aspects of firm operations, such as quality management (ISO 9001) or workplace safety (OHSAS 18001). However, as noted by Heras-Saizarbitoria and Boiral (2013), they are similar with regard to the methodology used for their creation, implementation, and monitoring.

To be more concrete, let us consider the case of the standard ISO 9001, which is the oldest and most popular process standard. To comply with it, firms must produce documentation describing the processes related to the creation of their product. Those documents must indicate the responsibilities of the senior management regarding quality, how resources will be procured and allocated to those processes, and how compliance with the documented procedures will be verified. Additionally, firms have to establish a procedure to create new processes if needed; and must create a "quality manual", which is a document listing the other documents (similar to an index of processes).

Despite their importance in the business world, process standards have received little attention from economics scholars. Using a combination of matching and diff-in-diff, Volpe Martincus et al. (2010), Masakure et al. (2009), and Sun and Ouyang (2014) found that certifying a management standard has a positive effect on exports. Using a similar method, Bernini et al. (2017) also found a positive effect of certification exports, but no effect on productivity. Employing instrumental variables for identification and a sample of Vietnamese small and medium enterprises, Calza et al. (2019) find that certifying a management standard has a positive effect on productivity, particularly among firms with previous

[4]Also called meta-standards (Uzumeri (1997)) in the management literature.

innovation experience and from the most developed part of the country.

Management scholars have produced a notable amount of work on process standards.[5] One of the central questions in this field is whether their adoption actually induces changes in how firms operate and whether it increases performance. Studies on this topic have found mixed results and, as noted by Heras-Saizarbitoria and Boiral (2013), they have faced important challenges when assessing whether the relationships they find are of a causal nature.

Given that process standards do not prescribe specific modern management practices, why is it reasonable to expect that they will help to foster their adoption? The hypothesis behind this idea is that there is complementarity between the standards' requirements and the modern managerial practices related with monitoring, target-setting, and incentives described in the previous subsection. Once processes have been properly described and designed in such a way that their execution leaves a record behind, other management practices become easier to implement. For example, if the execution of the different processes of the firm does not leave information about what was done, who did it, and the results of those actions; then, it is not possible to monitor that processes, or to set verifiable performance goals. The following section presents a model that illustrates this intuition.

From a policy perspective, the key advantage of a subsidy for standards certification over other types of interventions that have been used to try to improve management is that it can be handled like any other subsidy. Implementing agencies do not need to create curricula of knowledge to teach because the content of the standards has already been created, tested, and codified. Additionally, the wide popularity of these standards allows the existence of a market of consultancy firms that can be hired by the beneficiaries to provide support. Their popularity has also incentivized the publication of easily accessible information about the adoption process, and its benefits and challenges.

3 Model

In this section, I present a simple model that illustrates the idea that in the presence of complementarity between two technologies, a subsidy to promote one of them (for example, process documentation required by process standards), can also help to promote the adoption of the other (for example, modern management practices). In the model, a firm adopts technologies in two periods, and the technologies adopted in those periods exhibit complementarity, meaning that technology upgrading in one moment increases the benefit of upgrading in the next one.

3.1 Setup

In this model, a *firm* uses a single input l and the production function $f(l) = Al^{\alpha}$ $(0 < \alpha < 1)$. It maximizes profit taking the prices of the product (p) and input (w) as given. This way, the problem of the firm is:

[5] Sampaio et al. (2009), Tarí et al. (2012), Heras-Saizarbitoria and Boiral (2013), and Boiral et al. (2018) are important reviews of this literature. Heras-Saizarbitoria et al. (2019) and Riaz et al. (2019) are recent contributions.

$$\max_{l} \quad pAl^{\alpha} - wl \tag{1}$$

The optimum level of input is given by $l = \left(\frac{\alpha p A}{w}\right)^{\frac{1}{1-\alpha}}$ and the corresponding operating profit (meaning, the profit without considering technological investments) is $A^{\frac{1}{1-\alpha}}b$ with $b := p^{\frac{1}{1-\alpha}} w^{\frac{-\alpha}{\alpha-1}} (\alpha^{\frac{\alpha}{1-\alpha}} - \alpha^{\frac{1}{1-\alpha}})$. A is the productivity provided by the technology used by the firms. For algebraic convenience I represent this productivity with the monotonically increasing transformation $\phi := A^{\frac{1}{1-\alpha}}$. [6]

The set of existing *technologies* is $\{t_0, t_1, t_2, ...\}$, and ϕ_{t_i} is the productivity provided by technology t_i ($\phi_{t_0} < \phi_{t_1} < \phi_{t_2} < ...$). The cost of adopting a new technology depends on the current technology of the firm. More specifically, for a firm that has already adopted technology t_i, which provides productivity ϕ_{t_i}, the cost of adopting technology t_j, which provides productivity ϕ_{t_j}, is $(\phi_{t_j} - \phi_{t_i})^2$.

The *timing* of actions is as follows: The firm is born with technology $T_0 \in \{t_0, t_1, t_2, ...\}$, which provides productivity ϕ_{T_0}, and has two periods to adopt new technologies before producing. The variables T_1 and T_2 represent the technologies adopted by the firms in periods 1 and 2. Naturally, their support is also the set of existing technologies $\{t_0, t_1, t_2, ...\}$ and they provide productivity ϕ_{T_1} and ϕ_{T_2} respectively. Given that adoption costs are sunk, it never makes sense for the company to downgrade its technology, hence that option is ruled out. After these two periods, the firm produces using the last technology adopted, and obtains the corresponding profit $\pi(\phi_{T_1}, \phi_{T_2})$, which is equal to the operating profit minus the cost of technological adoption.

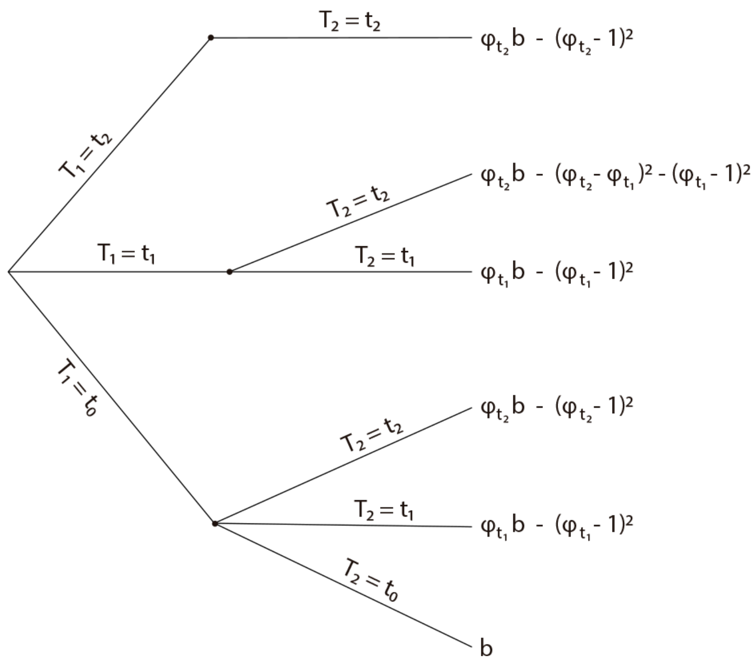
$$\pi(\phi_{T_1}, \phi_{T_2}) = \phi_{T_2} b - (\phi_{T_2} - \phi_{T_1})^2 - (\phi_{T_1} - \phi_{T_0})^2 \tag{2}$$

Note that in this setup, there is complementarity between the technologies adopted in different periods: The better the technology adopted in the first period, the higher the marginal benefit of technology upgrading in the second one. Formally, this means that the profit function is supermodular in (ϕ_{T_1}, ϕ_{T_2}). The proof of this property is in appendix I. At the core of this complementarity is the quadratic adoption cost, which represents the idea that big technological jumps are more costly than a series of incremental improvements.

For simplicity, let's consider the case in which there are three possible technologies t_0, t_1, t_2 with productivities ϕ_{t_0}, ϕ_{t_1}, ϕ_{t_2} ($\phi_{t_0} < \phi_{t_1} < \phi_{t_2}$), the firm is born with technology $T_0 = t_0$, and the productivity of this initial technology is normalized to 1 ($\phi_{T_0} = \phi_{t_0} = 1$). The possible actions and payoffs are represented in figure 1.

[6] This is similar to the presentation of the model in Bustos (2011), in which the productivity parameter is graphically represented by a monotonically increasing transformation.

Figure 1: Possible actions and their payoff



Different actions could be optimal for the firm depending on the specific values of the parameters ϕ_{t_1} and ϕ_{t_2}.

3.2 Exploiting complementarity to promote upgrading

In this subsection I show that, given an initial situation with no technological upgrading, a subsidy for the adoption of a simple technology can be used to foster the adoption of a more advanced one.

Consider a situation in which the following two conditions hold:

$$\phi_{t_2} b - (\phi_{t_2} - \phi_{t_1})^2 - (\phi_{t_1} - 1)^2 > \phi_{t_1} b - (\phi_{t_1} - 1)^2 \tag{3}$$

$$b > \phi_{t_2} b - (\phi_{t_2} - \phi_{t_1})^2 - (\phi_{t_1} - 1)^2 \tag{4}$$

In this case, the firm would keep technology t_0 until production time; despite the fact that, if it upgraded to t_1 in period 1, it would also update to t_2 in period 2.[7]

Now consider a subsidy S for the adoption of technology t_1 in period 1. Naturally, the value of this subsidy can be at most the cost of adopting this technology in the first period, $S < (\phi_{t_1} - 1)^2$. If S were at least $b - \phi_{t_2} b + (\phi_{t_2} - \phi_{t_1})^2 + (\phi_{t_1} - 1)^2$, the direction of the inequality in condition (4) would change, and the firm would adopt t_1 *and* t_2.

Note that for this to be possible, it has to be the case that $b - \phi_{t_2} b + (\phi_{t_2} - \phi_{t_1})^2 + (\phi_{t_1} - 1)^2 < (\phi_{t_1} - 1)^2$ which is equivalent to $\phi_{t_2} < \frac{1}{2}\left(\sqrt{b(b + 4\phi_{t_1} - 4)} + b + 2\phi_{t_1}\right)$. This inequality puts

[7]Note that $b > \phi_{t_1} b - (\phi_{t_1} - 1)^2$ and $b > \phi_{t_2} b - (\phi_{t_2} - 1)^2$ are implied conditions (3) and (4).

a limit on how far can ϕ_{t_2} be from ϕ_{t_1}. Intuitively, in order to exploit the complementarity, the final technology t_2 cannot be substantiatlly more advance than t_1.

Wouldn't be more convenient to simply subsidize the adoption of t_2? No. To induce the direct adoption of t_2, the magnitude of the subsidy S would need to be at least $b - \phi_{t_2} b + (\phi_{t_2} - 1)^2$, which is larger that the required subsidy to induce the adoption of t_1. Additionally, if t_1 represented process documentation and t_2 represented one of the modern management practices, subsidizing t_2 would be more difficult than subsidizing t_1.

In this subsection, I have shown how a small subsidy subsidy for the adoption of a simple technology can be used to foster the adoption of a more advanced one. In appendix H, I show that this type of intervention can be welfare improving if the initial situation exhibits market imperfections.

4 Empirical strategy

4.1 The Certification Program and the identification strategy

The certification program, which was implemented for the first time in 2015, is managed by *Innóvate Perú*, a Peruvian government agency in charge of programs to promote productive development. This program supports projects to certify process standards. Beneficiary firms receive a subsidy to cover up to 50% of the cost of the project, with a maximum of USD 14,000. Formal firms of any sector can apply provided that they had sales of less than USD 2.8 million the year before. In this analysis, I use data from the first three rounds (03/2015, 05/2015, and 10/2015). They include 250 applications, of which 127 were funded[8]. Table 1 reports descriptive statistics at the moment of application and compares them with country-level figures. Applicants were, on average, 10 years old and were concentrated in the secondary and tertiary sectors. Micro- and small-sized firms accounted for 81% of the participants, and 89% of them came from the coastal region of the country, which is the most economically developed region. Successful applicants were slightly, larger and older than unsuccessful ones. Compared with national figures, participants were larger, more focused on the secondary sector, and slightly more concentrated in coastal areas of the country.

[8]Appendix A provides details of sample construction.

Table 1: Baseline descriptive statistics

	Total (1)	Nontreated (2)	Treated (3)	National (4)
A. Sector				
primary	6.0%	5.7%	6.3%	2.3%
secondary	32.0%	29.3%	34.6%	11.0%
tertiary	62.0%	65.0%	59.1%	86.7%
B. Size				
micro	33.5%	37.9%	29.3%	94.6%
small	47.7%	44.0%	51.2%	4.4%
medium	18.8%	18.1%	19.5%	0.6%
C. Trade				
exported	13.2%	13.8%	12.6%	
imported	26.4%	26.0%	26.8%	
D. Other characteristics				
coast	88.8%	89.4%	88.2%	72.7%
age (yr)	10.2	9.5	10.9	

Column (1) shows percentages corresponding to the total of received applications, column (2) refers only to nonsubsidized applications, and column (3) refers to subsidized applications. Column (4) refers to national statistics recovered from the report *Perú: Estructura Empresarial 2015* prepared by the Peruvian national statistical institute (*Instituto Nacional de Estadística e Informática (INEI)*. The size classification is based on sales. In U.S. dollars, micro firms are those with sales between 0 and 190,000; small firms are those with sales between 190,000 and 2.1 million; medium firms are those with sales between 2.1 and 2.9 million.

To apply, firms submitted a project detailing their plan. Those projects were evaluated by external reviewers, who assigned them a score between 0 and 100 on four criteria: impact and relevance (35%), viability (25%), cost-benefit relationship (25%), and complementary factors (15%). The final score of the project was the average of those values. The subsidy was offered to projects with 70 points or more. I exploit this fact to implement a regression discontinuity analysis, using the score as the running variable. Figure 2a shows the treatment probability as a function of the running variable. It increases by approximately 80% at the cutoff. Figure 2b shows the distribution of the running variable. As can be seen, the score of the applications is a discrete variable. This is because reviewers used only a few salient values to evaluate the projects, and because only four criteria were assessed.

I estimate both intent-to-treat effects (ITT) and local average treatment effects (LATE) using local linear regressions.[9] To estimate ITT, I compute the OLS estimate of β_1 in the

[9] In this case, both ITT and LATE are local in the sense that that apply only to observations at the cutoff. LATE is additionally restricted to compliers.

following specification:

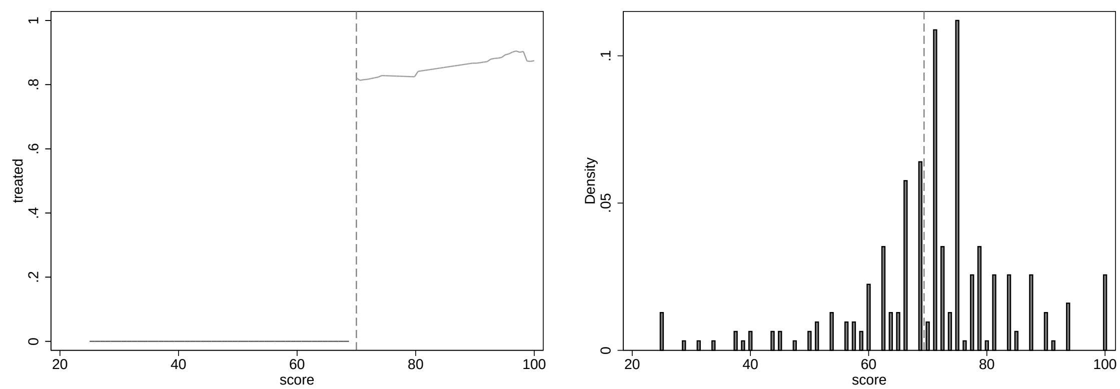
$$y = \beta_0 + \beta_1 \mathbf{1}(s \geq 70) + f(s) + u \tag{5}$$

where $\mathbf{1}(s \geq 70)$ is a dummy variable taking value one if the running variable s is to the right of the cutoff, $f(s)$ is polynomial of the running variable that allows for different slopes on different sides of the cutoff. To estimate LATE, I compute the IV estimate of β_1 in the following specification:

$$y = \beta_0 + \beta_1 treated + f(s) + u \tag{6}$$

where *treated* is a dummy variable that takes value one for treated observation. I instrument this variable with $\mathbf{1}(s \geq 70)$. In both cases, I use observations restricted to different bandwidths around the cutoff and uniform kernel.

Figure 2: Treatment probability and score distribution



(a) Treatment probability

(b) Score distribution

The graph on the left shows a local linear regression of a dummy variable that takes value one if a subsidy for the project was granted and zero otherwise, on the running variable. The local linear regression uses uniform kernel and a bandwidth of 20 points. The graph on the right shows the probability distribution of the running variable.

Although the discreteness of the running variable does not affect the identification arguments, it might be a challenge for inference, as noted by Lee and Card (2008) and Kolesár and Rothe (2018). The challenge is that in some cases, standard confidence intervals for treatment effects might have incorrect coverage when the running variable is discrete because the uncertainty about the behavior of the conditional expectation function between the running variable mass points is not eliminated even as the sample size grows. In practice, this is a problem only when the number of support points is small; hence, in general, there is no need to distinguish sharply between the discrete and continuous cases. However, to be cautious, I check that the conclusions obtained with the standard methods are robust to the use of methods that are not affected by the discreteness of the running variable. More specifically, I check the robustness of my results using the local randomization approach proposed by Cattaneo et al. (2015) and Cattaneo et al. (2018), and the "honest confidence intervals" proposed by Kolesár and Rothe (2018). The first approach consists of treating the observations in a narrow window around the cutoff as coming from an actual experiment and using finite sample randomized inference in that window to test the sharp null hypothesis of no effect. This renders the discreteness of the running variable irrelevant because the actual actual value of the running variable is not used after the window around the cutoff has been selected. In my estimations, I use different windows to show robustness. These windows are narrower than the bandwidths used for local linear regression because the local randomization assumption is stronger than the continuity one that underlies the usual procedure. The local randomization approach is my preferred alternative method because the use of finite sample inference methods makes it well suited to address my reduced sample size. The second approach consists of an alternative way to build confidence intervals. These honest confidence intervals have good coverage when the running variable is discrete provided that the underlying conditional expectation function is bounded, although they tend to be very broad.

4.2 Data sources

The main sources of data I use to study the certification program are the administrative records provided by *Innvóvate Perú*, the implementing agency, and a survey I ran in the last quarter of 2018. The administrative data contain some baseline information from the applications and their scores. The survey was administered to managers of the firms and was used to collect data about the certification of standards, the use of different management practices, and standard information about sales and employment.

To learn about the management practices of the firm, I asked a series of questions to assess management regarding monitoring, target-setting, and incentives. As mentioned by Bloom and Van Reenen (2010) these practices capture what is commonly understood as good management and are associated with high productivity and performance. Monitoring refers to the extent to which the activities that take place within the firms are supervised. A firm with good monitoring practices is one that systematically tracks and reviews the performance of different processes. Target-setting refers to the extent to which firms set explicit and verifiable goals. A company with sound target-setting practices is one that sets goals that are comprehensive and expressed in terms of variables that can be measured (as opposed to vague statements). The use of incentives refers to the extent in which an employee's effort is rewarded. Better incentive-related practices are those that allow the employee to benefit from the effort exerted.

To be more specific, monitoring was assessed with questions about whether the firm uses performance indicators, how many are used, and how often they are reviewed by managers. Target-setting was measured with questions about whether the firm uses explicit targets and the time-horizon considered. The information about incentives was collected by asking about the use of bonuses, worker reassignment and firing procedures, and promotion procedures. As in Bloom et al. (2019), I scored the answers to these questions with a variable taking value 0 if the practices are not used and 1 if it is used to a large extent. Then, I averaged those variables per type of practice. My management index is equal to the average of the scores for monitoring, target-setting, and incentives practices. Appendix B describes the construction of the index in more detail.

In addition to my main data sources, I also use trade data provided by the Chamber of

Peruvian Exporting Firms[10] and data manually collected from the tax authority's website. The trade data allow me to observe the export and import behavior of the companies and are provided through the commercial service ADEX Data Trade, which collects data from the customs administration and makes them accessible through a web-based interface. Form the tax authority's website, I collected information regarding firm's sector and age through the service called *Consulta RUC*. Appendix B also provides more details about how these additional data sources were used.

4.3 Validity of the identification strategy

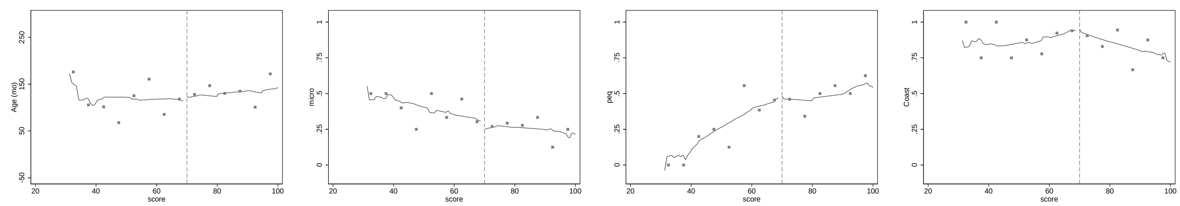
The validity of a regression discontinuity design as an identification strategy relies on the assumption that the value of the running variable has not been manipulated around the cutoff. In my case, firms cannot directly manipulate their score, so altering it would require some form of collusion between the firm and the reviewer. I do not believe that is a relevant concern in the case of the certification program, as the identity of the reviewer is decided after submitting the project and the firm never learns who that person was. Additionally, the implementing agency monitors that the project is actually executed and the money spent on it through on-site visits and requiring proof of payment and execution. This reduces the amount of resources that could be split between reviewer and firm-owner.

In addition to these considerations, the lack of manipulation has observable consequences that can be tested. In the absence of manipulation, there should not be discontinuities in the baseline covariates at the cutoff. Indeed, there is no evidence of such discontinuity. Figure 3 displays local linear regressions of different baseline covariates against the running variable, and shows that there is no evidence of an abrupt change at the cutoff value of the running variable. This is confirmed in table 2, which reports OLS estimates of the change in baseline characteristics at the cutoff using different bandwidths and polynomial degrees. None of the changes are statistically significant. Similarly, table 3 reports the mean difference of the baseline covariates between both sides of the cutoff and the randomized inference p-value of tests of the sharp null hypothesis of no difference. No significant difference is detected with this procedure and this conclusion is robust to the use of different windows around the threshold value. Appendix C that shows the conclusions are the same when using honest confidence intervals. Additionally, if manipulation did not occur, the running variable should be smoothly distributed around the cutoff. The usual practice is testing this using the McCrary (2008) test; however, this procedure is not valid when the running variable is discrete. An alternative test for the discrete case has been proposed by Frandsen (2016). This test compares the second differences around the cutoff with those occurring in other parts of the distribution. The null hypothesis is that the second differences in the cutoff area are not different from those occurring in other parts of the running variable's support. One of the disadvantages of this procedure compared with the McCrary (2008) test is that its ability to detect deviations from the null hypothesis decreases with the jaggedness of the running variable distribution. However, it is still informative that, in my case, this procedure fails to reject the null hypothesis of smoothness at the cutoff with a p-value of 0.648.[11]

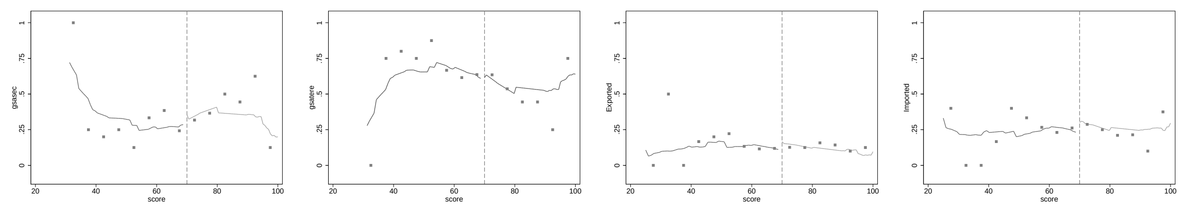
[10] *Asociación de Exportadores* (ADEX).

[11] To implement this test, the researcher has to provide the value of a parameter k measuring the degree

Figure 3: Continuity of baseline covariates



(a) Age (mo) **(b)** Micro **(c)** Small **(d)** Coast



(e) Manuf. **(f)** Services **(g)** Exported **(h)** Imported

Each of these graphs shows the local linear regression of a baseline covariate on the running variable, using a uniform kernel and a bandwidth of 20 points. In graph (a), the outcome variable is the age of the firm in months. In graph (b), it is a dummy variable that indicates the firm is a microfirm. In graph (c), it is a dummy variable that indicates the firm is a small firm. In graph (d), it is a dummy variable that indicates the firm is located in the coast region. In graph (e), it is a dummy variable that indicates the firm is classified in the manufacturing sector. In graph (f), it is a dummy variable that indicates the firm is classified in the service sector. In graph (g), it is a dummy variable that indicates that firm had exported. In graph (h), it is a dummy variable that indicates that the firm had imported.

---

of jaggedness of the running variable's probability function. Following Frandsen (2016), I based my choice of k on the behavior of the probability function away from the cutoff. More specifically, I computed k for all the support points, except the cutoff and its adjacent mass points, and used the average of those values in the test reported above. Additionally, as a robustness check, I also implemented the test using the average k in the full support, and the average k excluding only the cutoff value. In all these cases, the test fails to reject the null hypothesis of continuity.

Table 2: **Continuity of baseline covariates**

	(1) age (mo)	(2) micro	(3) small	(4) manuf.	(5) services	(6) coast	(7) export	(8) import
A. bw=10								
right	-17.014	-0.028	0.109	0.098	-0.019	0.005	-0.025	0.044
	(21.091)	(0.175)	(0.169)	(0.153)	(0.161)	(0.097)	(0.115)	(0.142)
obs	122	122	122	122	122	122	122	122
B. bw=20								
right	8.038	-0.045	-0.022	0.027	0.046	-0.018	-0.019	0.053
	(20.382)	(0.127)	(0.132)	(0.121)	(0.130)	(0.064)	(0.088)	(0.110)
obs	160	160	160	160	160	160	160	160
C. bw=30								
right	3.261	-0.032	-0.029	0.112	-0.050	-0.012	-0.047	-0.063
	(17.904)	(0.115)	(0.118)	(0.111)	(0.120)	(0.059)	(0.077)	(0.101)
obs	179	179	179	179	179	179	179	179
D. Full sample								
right	6.257	-0.028	-0.044	0.142	-0.086	-0.013	-0.030	-0.085
	(17.866)	(0.109)	(0.112)	(0.107)	(0.116)	(0.059)	(0.079)	(0.098)
obs	183	183	183	183	183	183	183	183
E. Full sample, cubic polynomial								
right	4.129	-0.093	0.172	0.264	-0.196	-0.007	0.156	0.231
	(28.053)	(0.196)	(0.195)	(0.173)	(0.178)	(0.109)	(0.138)	(0.159)
obs	183	183	183	183	183	183	183	183

***, **, * indicate significance at 1%, 5%, and 10%. The values reported in this table are the OLS estimates of β_1 in equation (5) taking the variable indicated at the top as the dependent variable. Values in parenthesis are standard errors clustered at the level of the firm. Panels A - C report estimates using a bandwidth of 10, 20, and 30 points around the cutoff, uniform kernel, and a linear polynomial of the running variable. Panel D reports similar estimates using the full sample. Panel E reports similar estimates using the full sample and a cubic polynomial of the running variable.

Table 3: **Continuity of baseline covariates**

	(1) age (mo)	(2) micro	(3) small	(4) manuf.	(5) services	(6) coast	(7) export	(8) import
A. Two mass points								
diff. in means	-4.021	0.021	0.102	0.160	-0.026	0.031	0.079	0.086
rand. inf. p-value	0.820	1.000	0.615	0.258	1.000	1.000	0.502	0.564
obs	58	58	58	58	58	58	58	58
B. 67.5 - 72.5								
diff. in means	-0.116	-0.162	0.116	0.157	-0.185	0.003	0.021	0.132
rand. inf. p-value	0.994	0.335	0.551	0.326	0.216	1.000	1.000	0.339
obs	53	53	53	53	53	53	53	53
C. 65 - 75								
diff. in means	10.192	-0.033	0.006	0.075	-0.001	-0.035	-0.026	-0.020
rand. inf. p-value	0.616	0.806	1.000	0.496	1.000	0.718	0.719	1.000
obs	96	96	96	96	96	96	96	96
D. 62.5 - 72.5								
diff. in means	16.944	-0.071	0.026	0.049	-0.019	-0.035	-0.037	-0.039
rand. inf. p-value	0.307	0.530	0.830	0.666	1.000	0.744	0.779	0.820
obs	111	111	111	111	111	111	111	111

In each panel of this table, each column reports three values. The first value is the mean difference of the variable indicated at the top between observations located to the left and right of the cutoff. The second value is the randomized inference p-value of a test of the sharp null hypothesis that the difference is zero. The third value is the number of observations. Estimates in panel A use only observations within two mass points of the cutoff, the narrowest window in which the test can be implemented. Estimates in panels B, C, and D use windows with radius of 2.5, 5, and 7.5 points.

5 Effects of the certification program

In this section, I show that the certification program accomplished its stated goal of promoting the certification of process standards and, additionally, induced the improvement of management practices beyond the scope of the certification. Moreover, I also provide evidence suggesting that the reason for the additional managerial improvement is the complementarity between the certification requirements and the management practices adopted. Regarding productivity, I find large positive effects, although they are not statistically significant at the conventional levels.

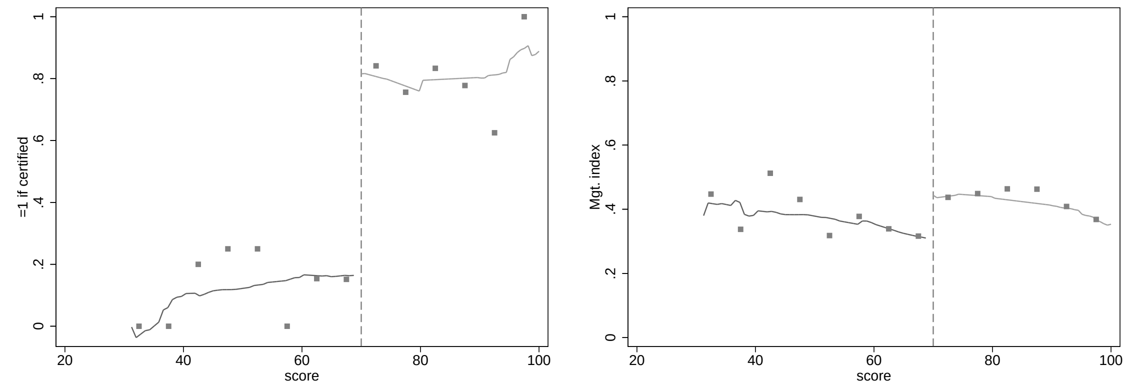
5.1 Effects on certification and management practices

I find that assignment to treatment increased the probability of certifying a process standard by approximately 65 percentage points, compared with a certification probability of 17% among non-treated firms. Figure 4a shows the result of a linear local regression of a dummy variable indicating that the standard certification was obtained, on the running variable. The vertical axis indicates the probability of being certified, the horizontal axis displays the running variable, and the dashed vertical line indicates the cutoff value. The increase in the treatment probability is apparent, and the estimates in table 4 confirm this finding. Columns 1 - 3 in table 4 report OLS and 2SLS estimates of the ITT and LATE of interest using local linear regression for bandwidths 10, 20, and 30. Columns 4 and 5 report similar estimates using the full sample with linear and cubic polynomials. Finally, columns 6 - 8 report the p-values of randomized inference tests using observations in different narrow windows around the cutoff. In column 6, only observations located within two running variable mass points of the cutoff are used. In columns 7 and 8, observations within 5 and 7.5 points, respectively are considered.

Consistent with the hypothesis of complementarity between process standards and modern management practices, I also find that assignment to treatment increases the management index, which varies between 0 and 1, by approximately 0.13 points. This is a sizable increase. Its value is equal to 33% of the mean value of the management index in 2018 and equal to 35% of the difference between the 25th and 75th percentiles of its distribution. The increase in the management index is graphically reported in figure 4b, and formally corroborated in table 5, which follows a format similar to the previous table. A potential concern with interpreting the positive estimate of the effect of the program on the management index as supporting the complementarity hypothesis is that this effect could also be explained by the fact that the subsidy represented an increase in income for firms that would have sought the certification regardless of their treatment status. Although it is not possible to rule out the existence of this income effect, I believe it does not drive the effect on management as the proportion of always-takers is just around 17% according to the proportion of non-treated firms that certified process standards.[12]

[12] A similar concern is discussed by Duflo et al. (2019) in a study about the impact of high school scholarships in Ghana.

Figure 4: Effect on certification and management index



(a) Certification **(b)** Management index

Each of these graphs shows a local linear regression of the dependent variable indicated below, on the running variable using a uniform kernel and a bandwidth of 20 points. The dots represent the mean of the outcome variable in 5-point bins. In the graph on the left, the dependent variable is a dummy variable that indicates whether the proposed certification was obtained. In the graph on the right, the outcome variable is the management index.

Table 4: Effect on certification probability

	Usual inference					Randomized inference		
	bw=10	bw=20	bw=30	full	full	w=2mp	w=5	w=7.5
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. ITT estimate								
right	0.689***	0.654***	0.620***	0.607***	0.590***	0.655	0.690	0.642
	(0.135)	(0.100)	(0.089)	(0.084)	(0.157)			
rand. inf. p-val.						0.000	0.000	0.000
B. LATE estimates								
treated	0.824***	0.798***	0.734***	0.720***	0.777***			
	(0.148)	(0.115)	(0.100)	(0.094)	(0.190)			
C. First stage								
right	0.837***	0.819***	0.844***	0.844***	0.759***			
	(0.080)	(0.054)	(0.047)	(0.047)	(0.099)			
F-stat	108.961	232.313	329.115	329.115	58.810			
obs	122	160	179	183	183	58	96	111

***, **, * indicate significance at 1%, 5%, and 10%. The estimates reported in panels A and B of this table correspond to the effect of the treatment on a dummy variable that indicates if the proposed certification was obtained. In panel A, columns 1 - 5 report OLS estimates of β_1 in equation (5). In panel B, these columns report the IV estimates of β_1 in equation (6). In panel C, they report the estimates of the first stage corresponding to the IV estimates in panel B. The F-stat of that first stage is reported below panel C. The values in parentheses are standard errors clustered at the level of the firm. Estimates in columns 1, 2 and 3 use bandwidths of 10, 20, and 30 points respectively, uniform kernel, and linear polynomial. Column 4 reports similar estimates using the full sample. Column 5 reports similar estimates using the full sample and a cubic polynomial. Columns 6 - 8 in panel A report two values. The first value is the mean difference of the dependent variable between observations located to the left and right of the cutoff. The second value is the randomized inference p-value of a test of the sharp null hypothesis that the effect of the dependent variable is zero. Estimates in column 6 use observations within two mass points of the cutoff. Estimates in columns 7 and 8 use observations within 5 and 7.5 points of the cutoff.

Table 5: Effect on management index

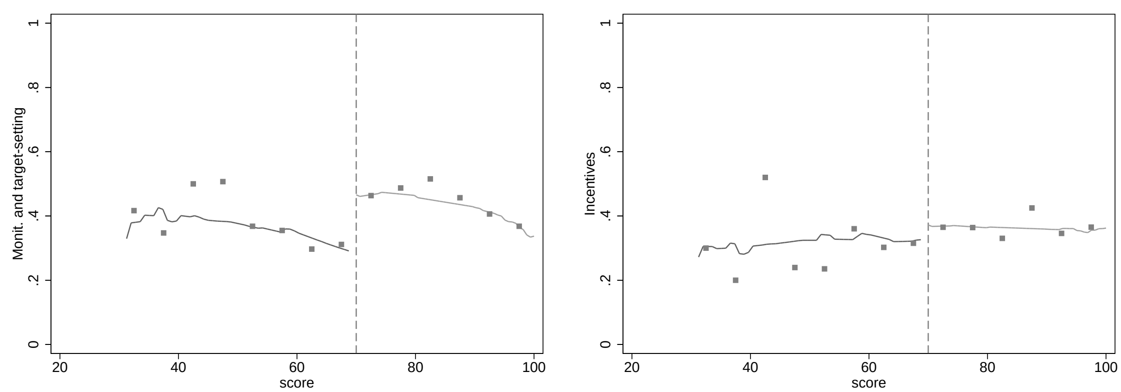
	Usual inference					Randomized inference		
	bw=10	bw=20	bw=30	full	full	w=2mp	w=5	w=7.5
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. ITT estimate								
right	0.134*	0.129**	0.164***	0.148***	0.181**	0.140	0.121	0.115
	(0.081)	(0.064)	(0.058)	(0.057)	(0.090)			
rand. inf. p-val.						0.033	0.020	0.014
B. LATE estimates								
treated	0.160*	0.158**	0.195***	0.175**	0.239**			
	(0.097)	(0.078)	(0.069)	(0.068)	(0.122)			
C. First stage								
right	0.837***	0.819***	0.844***	0.844***	0.759***			
	(0.080)	(0.054)	(0.047)	(0.047)	(0.099)			
F-stat	108.961	232.313	329.115	329.115	58.810			
obs	122	160	179	183	183	58	96	111

***, **, * indicate significance at 1%, 5%, and 10%. The estimates reported in panels A and B of this table correspond to the effect of the treatment on the management index. In panel A, columns 1 - 5 report OLS estimates of β_1 in equation (5). In panel B, these columns report the IV estimates of β_1 in equation (6). In panel C, they report the estimates of the first stage corresponding to the IV estimates in panel B. The F-stat of that first stage is reported below panel C. The values in parentheses are standard errors clustered at the level of the firm. Estimates in columns 1, 2 and 3 use bandwidths of 10, 20, and 30 points respectively, uniform kernel, and linear polynomial. Column 4 reports similar estimates using the full sample. Column 5 reports similar estimates using the full sample and a cubic polynomial. Columns 6 - 8 in panel A report two values. The first value is the mean difference of the dependent variable between observations located to the left and right of the cutoff. The second value is the randomized inference p-value of a test of the sharp null hypothesis that the effect of the dependent variable is zero. Estimates in column 6 use observations within two mass points of the cutoff. Estimates in columns 7 and 8 use observations within 5 and 7.5 points of the cutoff.

If the complementarity between process standards and modern management practices is one of the reasons why the certification program improved management quality, it would be reasonable to expect that an important part of the improvement is explained by changes in practices closely related to process standardization and documentation. To check if this is the case, I divide the management index into two subindices: one containing information about monitoring and target-setting and the other one containing information about incentives for employees. The practices included in the first subindex rely more heavily on the availability of process-level information than do the practices included in the second subindex, and are expected to react more intensely if complementarity is playing a role. Consider, for example, the case of performance indicators. Using performance indicators is part of having a good monitoring system. To build such indicators, managers must be able to gather information about the processes they want to monitor and to summarize that information in one or more numbers. Process standardization and documentation make it easier to construct those indicators because they help to delimit the different tasks and require leaving records that can later be used to collect the information required. This way, even though adopting a process standard is not the same as having a good monitoring system in place, the former eases the challenge of adopting the latter. Unlike monitoring and target-setting practices, incentive practices require not only information but also other changes such as modifying contracts with employees, which are not provided by a process standard.

As expected, the improvement in the overall management index occurred due to improvements in monitoring and target-setting, while no change is detected in incentives for employees. This difference is apparent in figures 5a and 5b, and is corroborated in tables 6 and 7.

Figure 5: Effect on monitoring & target-setting, and incentives



(a) Monitoring & target-setting

(b) Incentives

Each of these graphs shows the estimates of a local linear regression of the dependent variable on the running variable using a uniform kernel and a bandwidth of 20 points. The dots represent the mean of the outcome variable in 5-point bins. In the graph on the left, the dependent variable is the subindex of monitoring and target-setting practices. In the graph on the right, the outcome variable is the subindex of incentive practices.

Table 6: Effect on monitoring & target-setting

	Usual inference					Randomized inference		
	bw=10	bw=20	bw=30	full	full	w=2mp	w=5	w=7.5
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. ITT estimate								
right	0.137*	0.176***	0.211***	0.191***	0.170*	0.153	0.152	0.156
	(0.082)	(0.064)	(0.059)	(0.058)	(0.090)			
rand. inf. p-val.						0.022	0.006	0.002
B. LATE estimates								
treated	0.164*	0.214***	0.250***	0.226***	0.225*			
	(0.099)	(0.080)	(0.071)	(0.070)	(0.124)			
C. First stage								
right	0.837***	0.819***	0.844***	0.844***	0.759***			
	(0.080)	(0.054)	(0.047)	(0.047)	(0.099)			
F-stat	108.961	232.313	329.115	329.115	58.810			
obs	122	160	179	183	183	58	96	111

***, **, * indicate significance at 1%, 5%, and 10%. The estimates reported in panels A and B of this table correspond to the effect of the treatment on the the subindex of monitoring and target-setting practices. In panel A, columns 1 - 5 report OLS estimates of β_1 in equation (5). In panel B, these columns report the IV estimates of β_1 in equation (6). In panel C, they report the estimates of the first stage corresponding to the IV estimates in panel B. The F-stat of that first stage is reported below panel C. The values in parentheses are standard errors clustered at the level of the firm. Estimates in columns 1, 2 and 3 use bandwidths of 10, 20, and 30 points respectively, uniform kernel, and linear polynomial. Column 4 reports similar estimates using the full sample. Column 5 reports similar estimates using the full sample and a cubic polynomial. Columns 6 - 8 in panel A report two values. The first value is the mean difference of the dependent variable between observations located to the left and right of the cutoff. The second value is the randomized inference p-value of a test of the sharp null hypothesis that the effect of the dependent variable is zero. Estimates in column 6 use observations within two mass points of the cutoff. Estimates in columns 7 and 8 use observations within 5 and 7.5 points of the cutoff.

Table 7: **Certification - Effect on incentives**

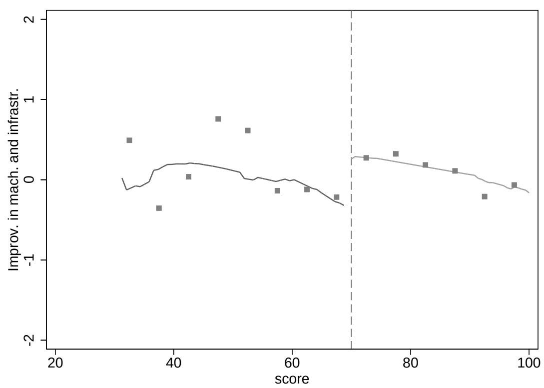
	Usual inference					Randomized inference		
	bw=10	bw=20	bw=30	full	full	w=2mp	w=5	w=7.5
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. ITT estimate								
right	0.052	0.039	0.073	0.048	0.091	0.060	0.050	0.048
	(0.094)	(0.074)	(0.070)	(0.066)	(0.112)			
rand. inf. p-val.						0.446	0.386	0.339
B. LATE estimates								
treated	0.062	0.048	0.086	0.057	0.120			
	(0.111)	(0.090)	(0.082)	(0.078)	(0.147)			
C. First stage								
right	0.837***	0.819***	0.844***	0.844***	0.759***			
	(0.080)	(0.054)	(0.047)	(0.047)	(0.099)			
F-stat	108.961	232.313	329.115	329.115	58.810			
obs	122	160	179	183	183	58	96	111

***, **, * indicate significance at 1%, 5%, and 10%. The estimates reported in panels A and B of this table correspond to the effect of the treatment on the subindex of incentives. In panel A, columns 1 - 5 report OLS estimates of β_1 in equation (5). In panel B, these columns report the IV estimates of β_1 in equation (6). In panel C, they report the estimates of the first stage corresponding to the IV estimates in panel B. The F-stat of that first stage is reported below panel C. The values in parentheses are standard errors clustered at the level of the firm. Estimates in columns 1, 2 and 3 use bandwidths of 10, 20, and 30 points respectively, uniform kernel, and linear polynomial. Column 4 reports similar estimates using the full sample. Column 5 reports similar estimates using the full sample and a cubic polynomial. Columns 6 - 8 in panel A report two values. The first value is the mean difference of the dependent variable between observations located to the left and right of the cutoff. The second value is the randomized inference p-value of a test of the sharp null hypothesis that the effect of the dependent variable is zero. Estimates in column 6 use observations within two mass points of the cutoff. Estimates in columns 7 and 8 use observations within 5 and 7.5 points of the cutoff.

5.2 Other changes within the firm

In addition to management upgrading, I also find evidence of improvements in the firms machinery and infrastructure. As part of the survey, I asked managers whether some changes had taken place between 2015 and 2018 in the following categories: i) changes in organizational structure, ii) changes in the workforce, iii) improvements in machinery and infrastructure, iv) reductions in production costs, v) changes in customers, vi) changes in suppliers. The details of the questions asked per category are presented in appendix G.1. I summarized their answers using the Kling et al. (2007) index, which is also used by Bruhn et al. (2018) for a similar purpose. This procedure consists in recentering the answer to each question at the mean of the control group, rescaling it by its standard deviation, and building the topic-level index as the average of those recentered and rescaled variables. Of the six categories of changes considered, I only find consistent evidence of impact for improvements in machinery and infrastructure. This can be seen in figure 6 and corroborated in table 8. The results for the other topics can be found in appendix G.2. Finding that the certification program led to an increase in the likelihood of improving machinery and infrastructure is consistent with the previous finding regarding managerial upgrading. As described in the literature review, the existing evidence suggests that the adoption of modern management practices boosts firm growth and that such effect occurs over long periods of time. If this process is indeed taking place, it would be reasonable to observe that, at least some the physical assets involved in the production process, are also been upgraded.

Figure 6: Effect on likelihood of improving machinery and infrastructure



This graph shows the estimates of a local linear regression of the Kling et al. (2007) index for improvements in machinery and infrastructure on the running variable using a uniform kernel and a bandwidth of 20 points. The dots represent the mean of the outcome variable in 5-point bins.

Table 8: Effect on likelihood of improving machinery and infrastructure

	Usual inference					Randomized inference		
	bw=10	bw=20	bw=30	full	full	w=2mp	w=5	w=7.5
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. ITT estimate								
right	0.512*	0.663***	0.616***	0.565***	0.524*	0.373	0.490	0.528
	(0.261)	(0.208)	(0.191)	(0.182)	(0.312)			
rand. inf. p-val.						0.084	0.013	0.002
B. LATE estimates								
treated	0.612*	0.810***	0.730***	0.670***	0.690			
	(0.316)	(0.261)	(0.230)	(0.219)	(0.424)			
C. First stage								
right	0.837***	0.819***	0.844***	0.844***	0.759***			
	(0.080)	(0.054)	(0.047)	(0.047)	(0.099)			
F-stat	108.961	232.313	329.115	329.115	58.810			
obs	122	160	179	183	183	58	96	111

***, **, * indicate significance at 1%, 5%, and 10%. The estimates reported in panels A and B of this table correspond to the effect of the treatment on the index of improvement in machinery and infrastructure. In panel A, columns 1 - 5 report OLS estimates of β_1 in equation (5). In panel B, these columns report the IV estimates of β_1 in equation (6). In panel C, they report the estimates of the first stage corresponding to the IV estimates in panel B. The F-stat of that first stage is reported below panel C. The values in parentheses are standard errors clustered at the level of the firm. Estimates in columns 1, 2 and 3 use bandwidths of 10, 20, and 30 points respectively, uniform kernel, and linear polynomial. Column 4 reports similar estimates using the full sample. Column 5 reports similar estimates using the full sample and a cubic polynomial. Columns 6 - 8 in panel A report two values. The first value is the mean difference of the dependent variable between observations located to the left and right of the cutoff. The second value is the randomized inference p-value of a test of the sharp null hypothesis that the effect of the dependent variable is zero. Estimates in column 6 use observations within two mass points of the cutoff. Estimates in columns 7 and 8 use observations within 5 and 7.5 points of the cutoff.

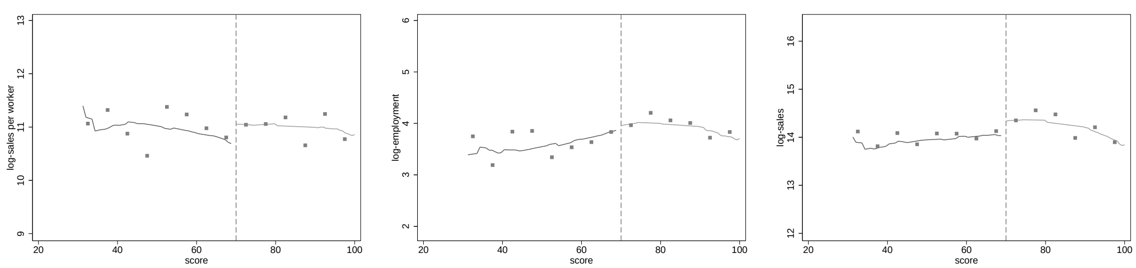
5.3 Effects on productivity and performance

Three years after treatment assignment, I find a positive, although statistically nonsignificant, effect of the certification program on productivity measured as log-sales per worker. The magnitude of this estimate is economically relevant. Columns 1 - 3 of table 9 report OLS and 2SLS estimates of the ITT and LATE using local linear regressions for bandwidths 10, 20, and 30. Columns 4 and 5 report similar results using full sample, and linear and cubic polynomials. These estimates are all positive, stable, but statistically nonsignificant at conventional levels even though their values are larger than their standard errors. Columns 6 - 8 in table 9 report randomized inference p-values for the ITT and indicate that the sharp null hypothesis of zero effect is rejected for the narrowest window around the cutoff, although this significance is lost for larger windows. Figure 7a shows the estimates of a local linear regression of log-sales per worker on the running variable. A small discontinuity can be seen at the cutoff, which is consistent with the OLS estimates of the ITT, and the randomized inference findings for observations close to the threshold value of the running variable. Regarding sales and employment, I find no evidence of impact as seen in figures 7b and 7c. Tables in appendix D report estimates and formal tests for these effects. These estimates are noisier than in the case of productivity.

The magnitude of the ITT estimates of the effect of the program on productivity oscillates around an increase of 40%.[13] Figure 8 puts this value the context of other papers in the literature. The vertical axis of this graph shows the percentage change in productivity or profitability estimated by other studies on management-enhancing interventions. The horizontal axis indicates the time elapsed since treatment assignment. The solid markers indicate estimates that are significant at conventional levels. The magnitude of the estimate in this paper is similar to those of previous studies.

The fact that the effect of the program on productivity is hard to detect despite the size and stability of the estimates is consistent with previous studies in the literature. Papers have shown that the effect of management-enhancing interventions on productivity and performance develops over several years and is difficult to detect shortly after treatment. For example, Giorcelli (2019) finds that the impact of the U.S. management support for Italian firms continued growing even 15 years after treatment assignment. Similarly, Bruhn et al. (2018) are able to detect the effect of a subsidy for management consulting on employment only six years after assignment.

Figure 7: Effect on productivity and performance



(a) log-sales per wkr. **(b)** log-employment **(c)** log-sales

Each of these graphs shows the estimates of a local linear regression of the dependent variable on the running variable using a uniform kernel and a bandwidth of 20 points. The dots represent the mean of the outcome variable in 5-point bins. In the graph on the left, the dependent variable is log-sales per worker. In the graph in the center, the outcome variable is log-employment (headcount), and in the graph on the right, the outcome variable is log-sales. Dependent variables were winsorized at the 10th and 90th percentiles to control for outliers.

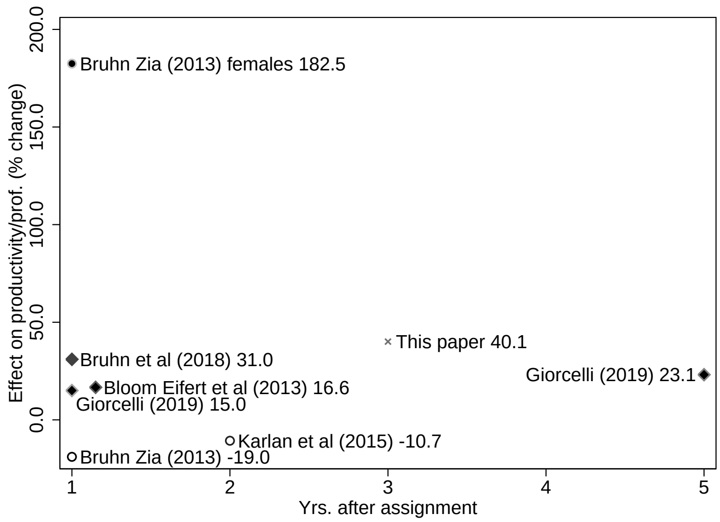
[13] 100*(exp(0.337)-1)=40

Table 9: Effect on log-sales per worker

	Usual inference					Randomized inference		
	bw=10	bw=20	bw=30	full	full	w=2mp	w=5	w=7.5
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. ITT estimate								
right	0.337	0.413	0.310	0.303	0.504	0.444	0.238	0.289
	(0.323)	(0.272)	(0.252)	(0.236)	(0.361)			
rand. inf. p-val.						0.082	0.270	0.134
B. LATE estimates								
treated	0.402	0.505	0.367	0.359	0.664			
	(0.387)	(0.333)	(0.298)	(0.280)	(0.481)			
C. First stage								
right	0.837***	0.819***	0.844***	0.844***	0.759***			
	(0.080)	(0.054)	(0.047)	(0.047)	(0.099)			
F-stat	108.961	232.313	329.115	329.115	58.810			
obs	122	160	179	183	183	58	96	111

***, **, * indicate significance at 1%, 5%, and 10%. The estimates reported in panels A and B of this table correspond to the effect of the treatment on log-sales per worker, winsorized at the 10th and 90th percentiles. In panel A, columns 1 - 5 report OLS estimates of β_1 in equation (5). In panel B, these columns report the IV estimates of β_1 in equation (6). In panel C, they report the estimates of the first stage corresponding to the IV estimates in panel B. The F-stat of that first stage is reported below panel C. The values in parentheses are standard errors clustered at the level of the firm. Estimates in columns 1, 2 and 3 use bandwidths of 10, 20, and 30 points respectively, uniform kernel, and linear polynomial. Column 4 reports similar estimates using the full sample. Column 5 reports similar estimates using the full sample and a cubic polynomial. Columns 6 - 8 in panel A report two values. The first value is the mean difference of the dependent variable between observations located to the left and right of the cutoff. The second value is the randomized inference p-value of a test of the sharp null hypothesis that the effect of the dependent variable is zero. Estimates in column 6 use observations within two mass points of the cutoff. Estimates in columns 7 and 8 use observations within 5 and 7.5 points of the cutoff.

Figure 8: Comparing effects on productivity



This figure presents results estimates from other studies about the effect of interventions to improve management on measures of productivity or profitability. The estimates have been transformed to represent percentage changes. Solid markers represent estimates significant at conventional levels, and hollow markers represent non-significant estimates. The estimates from Bloom et al. (2013), Bruhn et al. (2018), and Giorcelli (2019) refer to effects on TFP. Original results are coefficients from regression that take log-TFP as the dependent variable. These coefficients have been transformed by applying the exponential function, subtracting one, and multiplying by 100 to obtain percentage changes. The estimate from this paper comes from column (1) in table 9, and the same transformation has been applied to it. Bruhn and Zia (2013) report absolute changes in profits. These were transformed by reexpressing them as percentages of the value of this variable in the control group. Karlan et al. (2015) report absolute changes in revenue minus expenses. This value has been reexpressed as percentages of the value of this variable in the control group.

In previous sections, I have argued that the certification program helped improve management by reducing the cost of adopting modern management practices. However, the large estimates of the effect of the certification program on productivity raise a question about the mechanism connecting the intervention and the managerial improvement described above. More specifically, it could be possible that the certification program led to an increase in productivity through channels other than management quality and then, the increase in productivity induced the adoption of modern managerial practices. To address this concern, I reestimate the effect of the program on the management index introducing productivity measured as sales per worker as a control in equations (5) and (6). The estimates corresponding to this specification are presented appendix F. These estimates are similar in magnitude to those presented before in table 5. The significance of the estimates is also preserved, except in the case of the smallest bandwidth which is expected given that the number of estimated parameters has increased and the sample size has remained small. Appendix F also reports similar estimates for the effect of the program on the management subindices and shows that they are also consistent with those presented above. These results suggest that the effect of the certification program on management practices is not operating through an increase in productivity.

6 Conclusion

In the last decade, several papers have shown that the use of certain modern management practices related to monitoring, target-setting, and provision of incentives to employees are important for firm growth. The lack of adoption of these practices has been regarded as one of the reasons behind the low firm productivity observed in developing countries. Until recently, the explanations for this lack of upgrading have mainly revolved around informational limitations: the fact that business-owners might not know about the existence of better practices or the profitability of adopting them. However, policy-feasible interventions addressing this constraint have shown mixed results regarding managerial upgrading and its effect on performance.

In this paper, I have tried to accomplish two goals. First, I have suggested that, in addition to informational constraints, adoption costs are also an important barrier to the adoption of better management practices. Second, I have proposed a policy-feasible way to reduce these costs: subsidizing the adoption of widely known process standards, such as ISO 9001. These standards require firms to standardize and document their internal processes. This requirement is different from adopting the modern management practices related with monitoring, target-setting, and incentives that have been associated with firm growth. However, I hypothesized that these standards might exhibit complementarity with at least some modern management practices. Under this hypothesis, promoting the adoption of standards would also be useful to promote managerial upgrading beyond their scope. The existence of complementarity between different firm practices (not specifically process documentation and what I have called modern management practices) has been suggested previously (Ichniowski et al. (1997), Brynjolfsson and Milgrom (2013)). My findings suggest that this insight can be leveraged for policy design.

Using a newly created data set and a regression discontinuity design in a real policy setting, I have found evidence consistent with the complementarity hypothesis. The Peruvian certification program, which subsidized the adoption and certification of process standards, was successful at accomplishing its stated goal of promoting certification, and also promoted managerial improvement in other dimensions. The managerial improvement was concentrated in practices related with monitoring and target setting.

Three years after treatment assignment, I also found a positive, although statistically non-significant, increase in productivity measured as sales per worker. The magnitude of this change is similar to other findings in the literature. At the same time, I have found no evidence of changes in employment and sales. The lack of effect on these variables, as well as the lack of precision of the estimates for productivity, are consistent with previous studies, which have shown that the effects of interventions to promote better management materialize over several years and are hard to detect shortly after treatment (McKenzie and Woodruff (2014), Giorcelli (2019), Bruhn et al. (2018), Higuchi et al. (2019)).

Further research regarding the potential of process standards as a tool to improve management is warranted, given the advantages such standards offer with respect to other intervention techniques previously studied from an implementation point of view. Subsidies for adoption of standards are simple to manage because they can be treated like any other subsidy, a type of intervention governments have experience dealing with. Additionally, monitoring project completion is simple because the certification is easily verifiable. Moreover, the cost of this type of intervention is within the reach of a government or development agency. The program I studied granted, at most, USD 14,000. This value is similar to that of the Mexican intervention studied by Bruhn et al. (2018) and significantly cheaper than those described by Bloom et al. (2013) and Giorcelli (2019). A natural next step in this research is to return to the field and collect a new round of data to determine whether the effect on productivity has consolidated, and whether improvements in performance have materialized.

References

Bernini, F., Figal Garone, L., and Maffioli, A. International Quality Certification: Signaling to Whom? Impact on Firm Performance in Latin America and the Caribbean. Mimeo, 2017.

Bloom, N. and Van Reenen, J. Measuring and Explaining Management Practices across Firms and Countries. *The Quarterly Journal of Economics*, 122(4):1351–1408, 2007.

Bloom, N. and Van Reenen, J. Why Do Management Practices Differ across Firms and Countries? *Journal of Economic Perspectives*, 24(1):203–24, 2010.

Bloom, N., Eifert, B., Mahajan, A., McKenzie, D., and Roberts, J. Does Management Matter? Evidence from India. *The Quarterly Journal of Economics*, 128(1):1–51, 2013.

Bloom, N., Sadun, R., and Van Reenen, J. Management as a Technology? NBER Working Paper 22327, 2016.

Bloom, N., Mahajan, A., McKenzie, D., and Roberts, J. Do Management Interventions Last? Evidence from India. NBER Working paper 24249, 2018.

Bloom, N., Brynjolfsson, E., Foster, L., Jarmin, R., Patnaik, M., Saporta-Eksten, I., and Van Reenen, J. What Drives Differences in Management Practices? *American Economic Review*, 109(5):1648–83, 2019.

Boiral, O., Guillaumie, L., Heras-Saizarbitoria, I., and Tayo Tene, C. V. Adoption and Outcomes of ISO 14001: A Systematic Review. *International Journal of Management Reviews*, 20(2):411–432, 2018.

Braun, B. Building Global Institutions: The Diffusion of Management Standards in the World Economy An Institutional Perspective. In *Linking Industries Across the World*. Ashgate, 2005.

Bruhn, M. and Zia, B. Stimulating Managerial Capital in Emerging Markets: The Impact of Business Training for Young Entrepreneurs. *Journal of Development Effectiveness*, 5 (2):232–266, 2013.

Bruhn, M., Karlan, D., and Schoar, A. The Impact of Consulting Services on Small and Medium Enterprises: Evidence from a Randomized Trial in Mexico. *Journal of Political Economy*, 126(2):635–687, 2018.

Brynjolfsson, E. and Milgrom, P. Complementarity in Organizations. In *The Handbook of Organizational Economics*, pages 11–55. Princeton University Press Princeton, 2013.

Bustos, P. Trade Liberalization, Exports, and Technology Upgrading: Evidence on the Impact of MERCOSUR on Argentinian Firms. *American Economic Review*, 101(1):304–40, 2011.

Cai, J. and Szeidl, A. Interfirm Relationships and Business Performance. *The Quarterly Journal of Economics*, 133(3):1229–1282, 2017.

Calza, E., Goedhuys, M., and Trifković, N. Drivers of Productivity in Vietnamese SMEs: The Role of Management Standards and Innovation. *Economics of Innovation and New Technology*, 28(1):23–44, 2019.

Cattaneo, M. D., Frandsen, B. R., and Titiunik, R. Randomization Inference in the Regression Discontinuity Design: An Application to Party Advantages in the US Senate. *Journal of Causal Inference*, 3(1):1–24, 2015.

Cattaneo, M. D., Idrobo, N., and Titiunik, R. A Practical Introduction to Regression Discontinuity Designs: Volume II. Mimeo, 2018.

Cirera, X. and Maloney, W. *The Innovation Paradox*. The World Bank, 2017.

Drexler, A., Fischer, G., and Schoar, A. Keeping It Simple: Financial Literacy and Rules of Thumb. *American Economic Journal: Applied Economics*, 6(2):1–31, 2014.

Duflo, E., Dupas, P., and Kremer, M. The Impact of Free Secondary Education: Experimental Evidence from Ghana. Mimeo. Stanford University, 2019.

Foster, A. D. and Rosenzweig, M. R. Microeconomics of Technology Adoption. *The Annual Review of Economics*, 2(1):395–424, 2010.

Frandsen, B. R. Party Bias in Union Representation Elections: Testing for Manipulation in the Regression Discontinuity Design when the Running Variable is Discrete. *Mimeo*, 2016.

Giné, X. and Mansuri, G. Money or Ideas? A Field Experiment on Constraints to Entrepreneurship in Rural Pakistan. Mimeo. World Bank., 2014.

Giorcelli, M. The Long-Term Effects of Management and Technology Transfers. *American Economic Review*, 109(1):121–52, 2019.

Goñi, E. and Maloney, W. F. Why Dont Poor Countries do R&D? Varying Rates of Factor Returns Across the Development Process. *European Economic Review*, 94:126–147, 2017.

Heras-Saizarbitoria, I. and Boiral, O. ISO 9001 and ISO 14001: Towards a Research Agenda on Management System Standards. *International Journal of Management Reviews*, 15(1): 47–65, 2013.

Heras-Saizarbitoria, I., Boiral, O., Arana, G., and Allur, E. OHSAS 18001 Certification and Work Accidents: Shedding Light on the Connection. *Journal of Safety Research*, 68:33–40, 2019.

Higuchi, Y., Mhede, E. P., and Sonobe, T. Short-and Medium-run Impacts of Management Training: An Experiment in Tanzania. *World Development*, 114:220–236, 2019.

Hsieh, C.-T. and Klenow, P. J. Misallocation and manufacturing tfp in china and india. *The Quarterly journal of economics*, 124(4):1403–1448, 2009.

Ichniowski, C., Shaw, K., and Prennushi, G. The Effects of Human Resource Management Practices on Productivity: A Study of Steel Finishing Lines. *The American Economic Review*, pages 291–313, 1997.

Karlan, D. and Valdivia, M. Teaching Entrepreneurship: Impact of Business Training on Microfinance Clients and Institutions. *Review of Economics and statistics*, 93(2):510–527, 2011.

Karlan, D., Knight, R., and Udry, C. Consulting and Capital Experiments with Microenterprise Tailors in Ghana. *Journal of Economic Behavior & Organization*, 118:281–302, 2015.

Kling, J. R., Liebman, J. B., and Katz, L. F. Experimental Analysis of Neighborhood Effects. *Econometrica*, 75(1):83–119, 2007.

Kolesár, M. and Rothe, C. Inference in Regression Discontinuity Designs with a Discrete Running Variable. *American Economic Review*, 108(8):2277–2304, 2018.

Lee, D. S. and Card, D. Regression Discontinuity Inference with Specification Error. *Journal of Econometrics*, 142(2):655–674, 2008.

Manova, K. Credit Constraints, Heterogeneous Firms, and International Trade. *Review of Economic Studies*, 80(2):711–744, 2012.

Masakure, O., Henson, S., and Cranfield, J. Standards and Export Pperformance in Developing Dountries: Evidence from Pakistan. *The Journal of International Trade & Economic Development*, 18(3):395–419, 2009.

McCrary, J. Manipulation of the Running Variable in the Regression Discontinuity Design: A Density Test. *Journal of econometrics*, 142(2):698–714, 2008.

McKenzie, D. and Woodruff, C. What are We Learning from Business Training and Entrepreneurship Evaluations around the Developing World? *The World Bank Research Observer*, 29(1):48–82, 2014.

McKenzie, D. and Woodruff, C. Business Practices in Small Firms in Developing Countries. *Management Science*, 63(9):2773–3145, 2017.

Riaz, H., Saeed, A., Baloch, M. S., Khan, Z. A., et al. Valuation of Environmental Management Standard ISO 14001: Evidence from an Emerging Market. *Journal of Risk and Financial Management*, 12(1):21, 2019.

Sampaio, P., Saraiva, P., and Guimarães Rodrigues, A. ISO 9001 Certification Research: Questions, Answers and Approaches. *International Journal of Quality & Reliability Management*, 26(1):38–58, 2009.

Sun, Y. and Ouyang, W. International Standards for Exporting Firms: Evidence from China. *Journal of Applied Business Research*, 30(6):1753, 2014.

Syverson, C. Product Substitutability and Productivity Dispersion. *Review of Economics and Statistics*, 86(2):534–550, 2004.

Syverson, C. What Determines Productivity? *Journal of Economic literature*, 49(2):326–65, 2011.

Tarí, J. J., Molina-Azorín, J. F., and Heras, I. Benefits of the ISO 9001 and ISO 14001 Standards: A Literature Review. *Journal of Industrial Engineering and Management*, 5 (2):297–322, 2012.

Uzumeri, M. V. ISO 9000 and Other Metastandards: Principles for Management Practice? *Academy of Management Perspectives*, 11(1):21–36, 1997.

Valdivia, M. Business Training Plus for Female Entrepreneurship? Short and Medium-Term Experimental Evidence from Peru. *Journal of Development Economics*, 113:33–51, 2015.

Volpe Martincus, C., Castresana, S., and Castagnino, T. ISO standards: A Certificate to Expand Exports? Firm-level Evidence from Argentina. *Review of International Economics*, 18(5):896–912, 2010.

A Certification Program sample

The administrative records of *Innóvate Perú* indicate that 250 applications were received and sent to reviewers to be evaluated in the first three rounds of the Certification Program. Firms could not request reconsideration of their applications, but could submit different projects. In the main text of the article, I consider all the applications received independently and use cluster standard errors at the level of the firm to avoid overestimating the precision of the estimates. This is a conservative approach as it makes more difficult to find any effect and avoids arbitrarily selecting observations. In the appendix E.1, I show that the results are the same if they are estimated using a restricted sample that includes only the first round in which the never-treated firms applied, and the first round in which the ever-treated won.

A possible concern could be that reviewers manipulated the score to benefit or obstruct firms applying more than once. This possibility can be tested by checking that the number of previous applications does not change discontinuously at the cutoff. As shown in table 10, the number of previous applications is not different between firms just to the left and right of the cutoff, suggesting that there is no manipulation. This table reports OLS estimates of the difference in this variable on different sides of the the cutoff using local linear regressions with different bandwidths (columns 1 - 3), and the full sample using a linear and a cubic polynomial (columns 4 and 5, respectively). The table also reports randomized inference p-values for different windows around the cutoff (columns 6 - 8).

Table 10: Balance of number of previous applications

	Usual inference					Randomized inference		
	bw=10 (1)	bw=20 (2)	bw=30 (3)	full (4)	full (5)	w=2mp (6)	w=5 (7)	w=7.5 (8)
right	-0.033 (0.198)	0.004 (0.138)	0.061 (0.143)	0.024 (0.112)	-0.158 (0.220)	0.012	0.030	0.041
rand. inf. p-val.						1.000	0.870	0.774
obs	172	219	240	250	250	75	129	153

***, **, * indicate significance at 1%, 5%, and 10%. The estimates reported in this table correspond to estimates of the difference in a variable indicating the number of previous applications by the same firm. Columns 1 - 5 report OLS estimates of β_1 in equation (5). The values in parentheses are standard errors clustered at the level of the firm. Estimates in columns 1, 2 and 3 use bandwidths of 10, 20, and 30 points respectively, uniform kernel, and linear polynomial. Column 4 reports similar estimates using the full sample. Column 5 reports similar estimates using the full sample and a cubic polynomial. Columns 6 - 8 report three values. The first value is the mean difference of the dependent variable between observations located to the left and right of the cutoff. The second value is the randomized inference p-value of a test of the sharp null hypothesis that the difference is zero. The third value is the number of observations Estimates in column 6 use observations within two mass points of the cutoff. Estimates in columns 7 and 8 use observations within 5 and 7.5 points of the cutoff.

B Management index and complementary data sources

The management index was build using information collected in the survey using a questionnaire suited for firms in the sample. The starting point to develop the questionnaire was the one used by the U.S. Census Bureau in the Management and Organizational Practices Survey (MOPS). The main changes with respect to that instrument were: In the MOPS, there were two different questions regarding the use of bonuses for managers, and two for non-managers. One asked whether they were used and the percentage of managers/non-managers that received it. The other asked about the criteria used to determine their value. I reduced these questions to one per type of worker asking whether bonuses were used and the criteria they were based on. Additionally, in the MOPS, there were questions regarding the use of production display boards, difficulty achieving targets, and review of performance indicators by non-managers. These questions were omitted to accommodate the smaller size of the firms in the sample and the fact that the sample includes non-manufacturing firms.

With the collected management information, I built nine variables with support $[0, 1]$ measuring the adoption of different practices. This variables were grouped in categories according to whether they relate with monitoring, target-setting, or incentives. The category-level average of those variables is the score for that category, and the average of those categories is the value of the management index.

The variables created and the way in which the answers were scored is as follows (variables 1 and 2 were use to measure monitoring, variable 3 was used to measure target-setting, and variables 4 to 9 were used to measure incentives).

1. Use and number of performance indicators. Does not use=0, use between 1-2 indicators=1/4, use between 3-5=1/2, use between 6-9=3/4, use 10 or more=1.

2. Frequency with which performance indicators are reviewed. Does not use=0, annually=1/6, once per semester=2/6, quarterly=3/6, monthly=4/6, weekly=5/6, daily=1.

3. Use of explicit targets and their time horizon. Does not set explicit goals=0, only short-run (less than a year)=1/3, only long run (more than a year)=2/3, both short- and long-run=1.

4. Use of bonuses for managers and criteria they are based on. Does not use=0, use and they based on firm performance=1/2, use and they are based on individual performance=1.

5. Use of bonuses for non-managers and criteria they are based on. Does not use=0, use and they based on firm performance=1/2, use and they are based on individual performance=1.

6. Promotion methods for managers. Did not promote=0, promoted based on factors other than performance (e.g. tenure, owners trust, etc.)=1/3, promoted based on performance and other factors (e.g. tenure, owners trust, etc.)=2/3, promoted based on ability and individual performance=1.

7. Promotion methods for non-managers. Did not promote=0, promoted based on factors other than performance (e.g. tenure, owners trust, etc.)=1/3, promoted based on performance and other factors (e.g. tenure, owners trust, etc.)=2/3, promoted based on ability and individual performance=1.

8. Time to reassign or to fire an under-performing manager. Did not reassign=0, more than six months after identifying the problem=1/2, six months or less after identifying the problem=1.

9. Time to reassign or to fire an under-performing non-manager. Did not reassign=0, more than six months after identifying the problem=1/2, six months or less after identifying the problem=1.

In the questions regarding promotion of personnel and firing of under-performing employees, the majority of firms indicated that such situation had not occurred in 2018. To construct the management index, I treated this answers as zeros. This is the same decision taken by the Census Bureau in 2015 with respect to skipped questions. The results are the same using an alternative specification in which these questions are simply omitted.

Table 11 shows that the management index is positively correlated with performance measures. This exercise is useful to validate the management index. More specifically, the table reports the estimates of γ_1 in the regression $y = \gamma_0 + \gamma_1 mgt + v$, where y is a measure of performance in 2018 (log-employment, log-sales, or a dummy variable indicating that the firm exported) and mgt is the management index.

Table 11: Correlation between performance and mgt. index

	log-employ.	log-sales	exported
mgt. index	2.071***	2.012***	0.248*
	(0.307)	(0.371)	(0.134)
Obs.	183	183	183

***, **, * indicate significance at 1%, 5%, and 10%. This table reports the OLS estimate in of γ_1 in the regression $y = \gamma_0 + \gamma_1 mgt + v$ where y is the variable indicated at the top of the corresponding column and mgt is the management index. The values in parentheses are standard errors clustered at the level of the firm.

As mentioned in the main body of the paper, in addition to the main sources of data, I also used trade information from the commercial service ADEX Data Trade and from the service *Consulta RUC* provided by the Tax Authority. From ADEX Data Trade, I manually downloaded information about the trade behavior of the firms in the sample because the service does not allow the use of the full customs data at once. Instead, firm-level information has to be looked for using the name or tax id of the company and manually downloaded in Excel spreadsheets. The trade data used in this paper comes from this source. From *Consulta RUC*, I manually downloaded information about the date in which the firms started operating and firm sector (which is reported using the ISIC rev. 3 classification). With the first piece of information I calculated the age of the firm at the moment of application. With the second piece of information I created the sector variables. The tax authority allows reporting more than one sector. This leads to some level of missclassification as some firms report activities in sectors that do not correspond to their main activity. For example, firms that manufacture goods and sell them might report wholesale or retail activities in addition to manufacturing. To overcome this problem, I considered that firms belonged to the service sector only if that was the only sector they reported, otherwise I gave priority to the non-service sector.

C Balance tests using honest confidence intervals

Table 12: Continuity of baseline covariates

	(1) age (mo)	(2) micro	(3) small	(4) manuf.	(5) services	(6) coast	(7) export	(8) import
A. Using M=0 (full sample)								
right	7.431	-0.043	-0.003	0.089	-0.022	-0.025	-0.028	-0.006
	[-13.823	[-0.180	[-0.153	[-0.044	[-0.160	[-0.104	[-0.126	[-0.128
	28.686]	0.095]	0.148]	0.222]	0.115]	0.053]	0.071]	0.115]
obs.	183	183	183	183	183	183	183	183
B. Using data-driven selection for M								
right	7.431	-0.227	0.225	0.089	-0.022	-0.027	-0.028	-0.006
	[-13.823	[-0.753	[-0.162	[-0.044	[-0.160	[-0.172	[-0.126	[-0.128
	28.686]	0.299]	0.612]	0.222]	0.115]	0.117]	0.071]	0.115]
half. bw.	38.8	4.5	8.0	38.8	38.8	17.1	38.8	38.8
obs.	183	68	111	183	183	148	183	183

This table reports the estimates of β_1 in equation equation (5) taking as dependent variable the one indicated at the top of the column, and the corresponding 90% honest confidence intervals computed with the method of Kolesár and Rothe (2018). The method requires the researcher to provide the value of a parameter M that measures the non-linearity of the CEF. In turn, this parameter determines the bandwidth accepted by the method. Kolesár and Rothe (2018) proposed a data-driven method to estimate a lower bound for M and panel B reports results using that value. In many cases the selected value was zero which implies using the full sample. Panel A reports results using the $M = 0$ for all dependent variables.

D Effect on employment and sales

Table 13: Certification - Effect on log-employment

	Usual inference					Randomized inference		
	bw=10	bw=20	bw=30	full	full	w=2mp	w=5	w=7.5
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. ITT estimate								
right	-0.290	0.063	0.201	0.202	-0.322	-0.127	0.132	0.175
	(0.347)	(0.280)	(0.257)	(0.245)	(0.391)			
rand. inf. p-val.						0.638	0.537	0.380
B. LATE estimates								
treated	-0.347	0.077	0.238	0.239	-0.425			
	(0.420)	(0.342)	(0.304)	(0.290)	(0.523)			
C. First stage								
right	0.837***	0.819***	0.844***	0.844***	0.759***			
	(0.080)	(0.054)	(0.047)	(0.047)	(0.099)			
F-stat	108.961	232.313	329.115	329.115	58.810			
obs	122	160	179	183	183	58	96	111

***, **, * indicate significance at 1%, 5%, and 10%. The estimates reported in panels A and B of this table correspond to the effect of the treatment on log-employment (headcount), winsorized at the 10th and 90th percentiles. In panel A, columns 1 - 5 report OLS estimates of β_1 in equation (5). In panel B, these columns report the IV estimates of β_1 in equation (6). In panel C, they report the estimates of the first stage corresponding to the IV estimates in panel B. The F-stat of that first stage is reported below panel C. The values in parenthesis are standard errors clustered at the level of the firm. Estimates in columns 1, 2 and 3 use bandwidths of 10, 20, and 30 points respectively, uniform kernel, and linear polynomial. Column 4 reports similar estimates using the full sample. Column 5 reports similar estimates using the full sample and a cubic polynomial. Columns 6 - 8 in panel A report two values. The first value is the mean difference of the dependent variable between observations located to the left and right of the cutoff. The second value is the randomized inference p-value of a test of the sharp null hypothesis that the effect of the dependent variable is zero. Estimates in column 6 uses observations within two mass points of the cutoff. Estimates in columns 7 and 8 use observations within 5 and 7.5 points of the cutoff.

Table 14: Certification - Effect on log-sales

	Usual inference					Randomized inference		
	bw=10	bw=20	bw=30	full	full	w=2mp	w=5	w=7.5
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. ITT estimate								
right	-0.020	0.314	0.368	0.350	0.060	0.125	0.223	0.328
	(0.369)	(0.300)	(0.277)	(0.264)	(0.411)			
rand. inf. p-val.						0.690	0.371	0.162
B. LATE estimates								
treated	-0.024	0.383	0.436	0.415	0.079			
	(0.441)	(0.365)	(0.327)	(0.313)	(0.540)			
C. First stage								
right	0.837***	0.819***	0.844***	0.844***	0.759***			
	(0.080)	(0.054)	(0.047)	(0.047)	(0.099)			
F-stat	108.961	232.313	329.115	329.115	58.810			
obs	122	160	179	183	183	58	96	111

***, **, * indicate significance at 1%, 5%, and 10%. The estimates reported in panels A and B of this table correspond to the effect of the treatment on log-sales, winsorized at the 10th and 90th percentiles. In panel A, columns 1 - 5 report OLS estimates of β_1 in equation (5). In panel B, these columns report the IV estimates of β_1 in equation (6). In panel C, they report the estimates of the first stage corresponding to the IV estimates in panel B. The F-stat of that first stage is reported below panel C. The values in parenthesis are standard errors clustered at the level of the firm. Estimates in columns 1, 2 and 3 use bandwidths of 10, 20, and 30 points respectively, uniform kernel, and linear polynomial. Column 4 reports similar estimates using the full sample. Column 5 reports similar estimates using the full sample and a cubic polynomial. Columns 6 - 8 in panel A report two values. The first value is the mean difference of the dependent variable between observations located to the left and right of the cutoff. The second value is the randomized inference p-value of a test of the sharp null hypothesis that the effect of the dependent variable is zero. Estimates in column 6 uses observations within two mass points of the cutoff. Estimates in columns 7 and 8 use observations within 5 and 7.5 points of the cutoff.

E Robustness of results

E.1 Results using the restricted sample

Table 15: Effect on certification probability

	Usual inference					Randomized inference		
	bw=10	bw=20	bw=30	full	full	w=2mp	w=5	w=7.5
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. ITT estimate								
right	0.649***	0.740***	0.714***	0.691***	0.494**	0.694	0.733	0.728
	(0.157)	(0.120)	(0.105)	(0.095)	(0.195)			
rand. inf. p-val.						0.000	0.000	0.000
B. LATE estimates								
treated	0.759***	0.855***	0.802***	0.776***	0.641***			
	(0.175)	(0.135)	(0.115)	(0.103)	(0.241)			
C. First stage								
right	0.854***	0.866***	0.890***	0.890***	0.772***			
	(0.078)	(0.051)	(0.044)	(0.044)	(0.098)			
F-stat	120.165	284.976	418.150	418.150	62.182			
obs	102	137	154	157	157	46	80	92

***, **, * indicate significance at 1%, 5%, and 10%. The estimates reported in panels A and B of this table correspond to the effect of the treatment on a dummy variable that indicates if the proposed certification was obtained. In panel A, columns 1 - 5 report OLS estimates of β_1 in equation (5). In panel B, these columns report the IV estimates of β_1 in equation (6). In panel C, they report the estimates of the first stage corresponding to the IV estimates in panel B. The F-stat of that first stage is reported below panel C. The values in parenthesis are standard errors clustered at the level of the firm. Estimates in columns 1, 2 and 3 use bandwidths of 10, 20, and 30 points respectively, uniform kernel, and linear polynomial. Column 4 reports similar estimates using the full sample. Column 5 reports similar estimates using the full sample and a cubic polynomial. Columns 6 - 8 in panel A report two values. The first value is the mean difference of the dependent variable between observations located to the left and right of the cutoff. The second value is the randomized inference p-value of a test of the sharp null hypothesis that the effect of the dependent variable is zero. Estimates in column 6 uses observations within two mass points of the cutoff. Estimates in columns 7 and 8 use observations within 5 and 7.5 points of the cutoff.

Table 16: Effect on management index

	Usual inference					Randomized inference		
	bw=10	bw=20	bw=30	full	full	w=2mp	w=5	w=7.5
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. ITT estimate								
right	0.175*	0.172**	0.200***	0.177**	0.248**	0.176	0.141	0.140
	(0.091)	(0.075)	(0.069)	(0.069)	(0.097)			
rand. inf. p-val.						0.016	0.020	0.008
B. LATE estimates								
treated	0.205*	0.199**	0.225***	0.199**	0.321**			
	(0.108)	(0.088)	(0.078)	(0.078)	(0.134)			
C. First stage								
right	0.854***	0.866***	0.890***	0.890***	0.772***			
	(0.078)	(0.051)	(0.044)	(0.044)	(0.098)			
F-stat	120.165	284.976	418.150	418.150	62.182			
obs	102	137	154	157	157	46	80	92

***, **, * indicate significance at 1%, 5%, and 10%. The estimates reported in panels A and B of this table correspond to the effect of the treatment on the management index. In panel A, columns 1 - 5 report OLS estimates of β_1 in equation (5). In panel B, these columns report the IV estimates of β_1 in equation (6). In panel C, they report the estimates of the first stage corresponding to the IV estimates in panel B. The F-stat of that first stage is reported below panel C. The values in parenthesis are standard errors clustered at the level of the firm. Estimates in columns 1, 2 and 3 use bandwidths of 10, 20, and 30 points respectively, uniform kernel, and linear polynomial. Column 4 reports similar estimates using the full sample. Column 5 reports similar estimates using the full sample and a cubic polynomial. Columns 6 - 8 in panel A report two values. The first value is the mean difference of the dependent variable between observations located to the left and right of the cutoff. The second value is the randomized inference p-value of a test of the sharp null hypothesis that the effect of the dependent variable is zero. Estimates in column 6 uses observations within two mass points of the cutoff. Estimates in columns 7 and 8 use observations within 5 and 7.5 points of the cutoff.

Table 17: Effect on monitoring & target-setting

	Usual inference					Randomized inference		
	bw=10	bw=20	bw=30	full	full	w=2mp	w=5	w=7.5
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. ITT estimate								
right	0.171*	0.215***	0.255***	0.220***	0.195*	0.188	0.178	0.182
	(0.090)	(0.073)	(0.066)	(0.066)	(0.100)			
rand. inf. p-val.						0.009	0.004	0.001
B. LATE estimates								
treated	0.200*	0.249***	0.287***	0.248***	0.253*			
	(0.108)	(0.085)	(0.075)	(0.076)	(0.135)			
C. First stage								
right	0.854***	0.866***	0.890***	0.890***	0.772***			
	(0.078)	(0.051)	(0.044)	(0.044)	(0.098)			
F-stat	120.165	284.976	418.150	418.150	62.182			
obs	102	137	154	157	157	46	80	92

***, **, * indicate significance at 1%, 5%, and 10%. The estimates reported in panels A and B of this table correspond to the effect of the treatment on the subdindex of monitoring and target-setting practices. In panel A, columns 1 - 5 report OLS estimates of β_1 in equation (5). In panel B, these columns report the IV estimates of β_1 in equation (6). In panel C, they report the estimates of the first stage corresponding to the IV estimates in panel B. The F-stat of that first stage is reported below panel C. The values in parenthesis are standard errors clustered at the level of the firm. Estimates in columns 1, 2 and 3 use bandwidths of 10, 20, and 30 points respectively, uniform kernel, and linear polynomial. Column 4 reports similar estimates using the full sample. Column 5 reports similar estimates using the full sample and a cubic polynomial. Columns 6 - 8 in panel A report two values. The first value is the mean difference of the dependent variable between observations located to the left and right of the cutoff. The second value is the randomized inference p-value of a test of the sharp null hypothesis that the effect of the dependent variable is zero. Estimates in column 6 uses observations within two mass points of the cutoff. Estimates in columns 7 and 8 use observations within 5 and 7.5 points of the cutoff.

Table 18: Effect on incentives

	Usual inference					Randomized inference		
	bw=10	bw=20	bw=30	full	full	w=2mp	w=5	w=7.5
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. ITT estimate								
right	0.205	0.148	0.107	0.134	0.381***	0.192	0.092	0.126
	(0.128)	(0.110)	(0.099)	(0.102)	(0.146)			
rand. inf. p-val.						0.126	0.431	0.205
B. LATE estimates								
treated	0.240	0.171	0.120	0.150	0.493**			
	(0.149)	(0.126)	(0.111)	(0.114)	(0.194)			
C. First stage								
right	0.854***	0.866***	0.890***	0.890***	0.772***			
	(0.078)	(0.051)	(0.044)	(0.044)	(0.098)			
F-stat	120.165	284.976	418.150	418.150	62.182			
obs	102	137	154	157	157	46	80	92

***, **, * indicate significance at 1%, 5%, and 10%. The estimates reported in panels A and B of this table correspond to the effect of the treatment on the subdindex of incentive practices. In panel A, columns 1 - 5 report OLS estimates of β_1 in equation (5). In panel B, these columns report the IV estimates of β_1 in equation (6). In panel C, they report the estimates of the first stage corresponding to the IV estimates in panel B. The F-stat of that first stage is reported below panel C. The values in parenthesis are standard errors clustered at the level of the firm. Estimates in columns 1, 2 and 3 use bandwidths of 10, 20, and 30 points respectively, uniform kernel, and linear polynomial. Column 4 reports similar estimates using the full sample. Column 5 reports similar estimates using the full sample and a cubic polynomial. Columns 6 - 8 in panel A report two values. The first value is the mean difference of the dependent variable between observations located to the left and right of the cutoff. The second value is the randomized inference p-value of a test of the sharp null hypothesis that the effect of the dependent variable is zero. Estimates in column 6 uses observations within two mass points of the cutoff. Estimates in columns 7 and 8 use observations within 5 and 7.5 points of the cutoff.

Table 19: Effect on log-sales per worker

	Usual inference					Randomized inference		
	bw=10	bw=20	bw=30	full	full	w=2mp	w=5	w=7.5
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. ITT estimate								
right	0.398	0.508	0.423	0.344	0.443	0.508	0.343	0.380
	(0.401)	(0.333)	(0.304)	(0.289)	(0.443)			
rand. inf. p-val.						0.093	0.204	0.123
B. LATE estimates								
treated	0.466	0.587	0.475	0.387	0.574			
	(0.471)	(0.387)	(0.343)	(0.325)	(0.580)			
C. First stage								
right	0.854***	0.866***	0.890***	0.890***	0.772***			
	(0.078)	(0.051)	(0.044)	(0.044)	(0.098)			
F-stat	120.165	284.976	418.150	418.150	62.182			
obs	102	137	154	157	157	46	80	92

***, **, * indicate significance at 1%, 5%, and 10%. The estimates reported in panels A and B of this table correspond to the effect of the treatment on log-sales per worker, winsorized at the 10th and 90th percentiles. In panel A, columns 1 - 5 report OLS estimates of β_1 in equation (5). In panel B, these columns report the IV estimates of β_1 in equation (6). In panel C, they report the estimates of the first stage corresponding to the IV estimates in panel B. The F-stat of that first stage is reported below panel C. The values in parenthesis are standard errors clustered at the level of the firm. Estimates in columns 1, 2 and 3 use bandwidths of 10, 20, and 30 points respectively, uniform kernel, and linear polynomial. Column 4 reports similar estimates using the full sample. Column 5 reports similar estimates using the full sample and a cubic polynomial. Columns 6 - 8 in panel A report two values. The first value is the mean difference of the dependent variable between observations located to the left and right of the cutoff. The second value is the randomized inference p-value of a test of the sharp null hypothesis that the effect of the dependent variable is zero. Estimates in column 6 uses observations within two mass points of the cutoff. Estimates in columns 7 and 8 use observations within 5 and 7.5 points of the cutoff.

Table 20: Effect on log-employment

	Usual inference					Randomized inference		
	bw=10	bw=20	bw=30	full	full	w=2mp	w=5	w=7.5
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. ITT estimate								
right	-0.056	0.269	0.354	0.366	0.095	0.094	0.270	0.312
	(0.366)	(0.299)	(0.279)	(0.265)	(0.434)			
rand. inf. p-val.						0.699	0.291	0.187
B. LATE estimates								
treated	-0.066	0.310	0.398	0.412	0.123			
	(0.429)	(0.343)	(0.313)	(0.296)	(0.561)			
C. First stage								
right	0.854***	0.866***	0.890***	0.890***	0.772***			
	(0.078)	(0.051)	(0.044)	(0.044)	(0.098)			
F-stat	120.165	284.976	418.150	418.150	62.182			
obs	102	137	154	157	157	46	80	92

***, **, * indicate significance at 1%, 5%, and 10%. The estimates reported in panels A and B of this table correspond to the effect of the treatment on log-employment (headcount), winsorized at the 10th and 90th percentiles. In panel A, columns 1 - 5 report OLS estimates of β_1 in equation (5). In panel B, these columns report the IV estimates of β_1 in equation (6). In panel C, they report the estimates of the first stage corresponding to the IV estimates in panel B. The F-stat of that first stage is reported below panel C. The values in parenthesis are standard errors clustered at the level of the firm. Estimates in columns 1, 2 and 3 use bandwidths of 10, 20, and 30 points respectively, uniform kernel, and linear polynomial. Column 4 reports similar estimates using the full sample. Column 5 reports similar estimates using the full sample and a cubic polynomial. Columns 6 - 8 in panel A report two values. The first value is the mean difference of the dependent variable between observations located to the left and right of the cutoff. The second value is the randomized inference p-value of a test of the sharp null hypothesis that the effect of the dependent variable is zero. Estimates in column 6 uses observations within two mass points of the cutoff. Estimates in columns 7 and 8 use observations within 5 and 7.5 points of the cutoff.

Table 21: Effect on log-sales

	Usual inference					Randomized inference		
	bw=10	bw=20	bw=30	full	full	w=2mp	w=5	w=7.5
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. ITT estimate								
right	0.189	0.557	0.602*	0.517	0.325	0.345	0.405	0.507
	(0.439)	(0.370)	(0.347)	(0.331)	(0.504)			
rand. inf. p-val.						0.332	0.177	0.066
B. LATE estimates								
treated	0.222	0.644	0.677*	0.581	0.421			
	(0.513)	(0.427)	(0.389)	(0.371)	(0.652)			
C. First stage								
right	0.854***	0.866***	0.890***	0.890***	0.772***			
	(0.078)	(0.051)	(0.044)	(0.044)	(0.098)			
F-stat	120.165	284.976	418.150	418.150	62.182			
obs	102	137	154	157	157	46	80	92

***, **, * indicate significance at 1%, 5%, and 10%. The estimates reported in panels A and B of this table correspond to the effect of the treatment on log-sales, winsorized at the 10th and 90th percentiles. In panel A, columns 1 - 5 report OLS estimates of β_1 in equation (5). In panel B, these columns report the IV estimates of β_1 in equation (6). In panel C, they report the estimates of the first stage corresponding to the IV estimates in panel B. The F-stat of that first stage is reported below panel C. The values in parenthesis are standard errors clustered at the level of the firm. Estimates in columns 1, 2 and 3 use bandwidths of 10, 20, and 30 points respectively, uniform kernel, and linear polynomial. Column 4 reports similar estimates using the full sample. Column 5 reports similar estimates using the full sample and a cubic polynomial. Columns 6 - 8 in panel A report two values. The first value is the mean difference of the dependent variable between observations located to the left and right of the cutoff. The second value is the randomized inference p-value of a test of the sharp null hypothesis that the effect of the dependent variable is zero. Estimates in column 6 uses observations within two mass points of the cutoff. Estimates in columns 7 and 8 use observations within 5 and 7.5 points of the cutoff.

E.2 Results using honest confidence intervals

Table 22: Results using honest confidence intervals

	(1) certif.	(2) mgt. index	(3) monit. & targ.	(4) incentives	(5) log-sales per wkr.	(6) log-employ.	(7) log-sales
A. Using M=0 (full sample)							
right	0.636	0.153	0.192	0.064	0.324	0.127	0.305
	[0.519	[0.086	[0.123	[-0.018	[0.027	[-0.175	[-0.026
	0.752]	0.219]	0.261]	0.146]	0.621]	0.429]	0.636]
obs.	183	183	183	183	183	183	183
B. Using data-driven selection for M							
right	0.636	0.286	0.254	0.064	0.324	-0.057	0.328
	[0.519	[0.097	[0.021	[-0.018	[0.027	[-0.588	[-0.577
	0.752]	0.476]	0.486]	0.146]	0.621]	0.473]	1.232]
half. bw.	38.8	5.7	5.1	38.8	38.8	17.5	6.9
obs.	183	96	96	183	183	152	99

This table reports the estimates of β_1 in equation equation (5) taking as dependent variable the one indicated at the top of the column, and the corresponding 90% honest confidence intervals computed with the method of Kolesár and Rothe (2018). The method requires the researcher to provide the value of a parameter M that measures the non-linearity of the CEF. In turn, this parameter determines the bandwidth accepted by the method. Appendix S.2 in Kolesár and Rothe (2018) proposed a data-driven method to estimate a lower bound for M and panel B reports results using that value. In many cases the selected value was zero which implies using the full sample. Panel A reports results using the $M = 0$ for all dependent variables.

F Effect on management index and subindices controlling for productivity

Table 23: Effect on management index controlling for productivity

	bw=10	bw=20	bw=30	full	full
	(1)	(2)	(3)	(4)	(5)
A. ITT estimate					
right	0.120	0.118*	0.160***	0.145**	0.177**
	(0.080)	(0.063)	(0.058)	(0.057)	(0.089)
B. LATE estimates					
treated	0.145	0.145*	0.189***	0.171**	0.232*
	(0.096)	(0.077)	(0.068)	(0.067)	(0.120)
C. First stage					
right	0.831***	0.818***	0.846***	0.846***	0.762***
	(0.080)	(0.054)	(0.047)	(0.047)	(0.099)
F-stat	107.770	231.539	329.624	329.652	59.214
obs	122	160	179	183	183

***, **, * indicate significance at 1%, 5%, and 10%. The estimates reported in panels A and B of this table correspond to the effect of the treatment on the management index controlling for log-sales per worker winsorized at the 10th and 90th percentiles. In panel A, columns 1 - 5 report OLS estimates of β_1 in equation (5) including log-sales per worker as a control. In panel B, these columns report the IV estimates of β_1 in equation (6) including log-sales per worker as a control. In panel C, they report the estimates of the first stage corresponding to the IV estimates in panel B. The F-stat of that first stage is reported below panel C. The values in parentheses are standard errors clustered at the level of the firm. Estimates in columns 1, 2 and 3 use bandwidths of 10, 20, and 30 points respectively, uniform kernel, and linear polynomial. Column 4 reports similar estimates using the full sample. Column 5 reports similar estimates using the full sample and a cubic polynomial.

Table 24: Effect on monitoring & target-setting controlling for productivity

	bw=10	bw=20	bw=30	full	full
	(1)	(2)	(3)	(4)	(5)
A. ITT estimate					
right	0.124	0.164***	0.204***	0.186***	0.163*
	(0.080)	(0.063)	(0.058)	(0.057)	(0.089)
B. LATE estimates					
treated	0.149	0.200**	0.242***	0.220***	0.213*
	(0.098)	(0.079)	(0.070)	(0.069)	(0.121)
C. First stage					
right	0.831***	0.818***	0.846***	0.846***	0.762***
	(0.080)	(0.054)	(0.047)	(0.047)	(0.099)
F-stat	107.770	231.539	329.624	329.652	59.214
obs	122	160	179	183	183

***, **, * indicate significance at 1%, 5%, and 10%. The estimates reported in panels A and B of this table correspond to the effect of the treatment on the subindex of monitoring and target-setting practices controlling for log-sales per worker winsorized at the 10th and 90th percentiles. In panel A, columns 1 - 5 report OLS estimates of β_1 in equation (5) including log-sales per worker as a control. In panel B, these columns report the IV estimates of β_1 in equation (6) including log-sales per worker as a control. In panel C, they report the estimates of the first stage corresponding to the IV estimates in panel B. The F-stat of that first stage is reported below panel C. The values in parentheses are standard errors clustered at the level of the firm. Estimates in columns 1, 2 and 3 use bandwidths of 10, 20, and 30 points respectively, uniform kernel, and linear polynomial. Column 4 reports similar estimates using the full sample. Column 5 reports similar estimates using the full sample and a cubic polynomial.

Table 25: **Effect on incentives controlling for productivity**

	bw=10	bw=20	bw=30	full	full
	(1)	(2)	(3)	(4)	(5)
A. ITT estimate					
right	0.045	0.037	0.078	0.054	0.101
	(0.093)	(0.074)	(0.070)	(0.066)	(0.112)
B. LATE estimates					
treated	0.054	0.046	0.092	0.063	0.132
	(0.112)	(0.090)	(0.082)	(0.078)	(0.146)
C. First stage					
right	0.831***	0.818***	0.846***	0.846***	0.762***
	(0.080)	(0.054)	(0.047)	(0.047)	(0.099)
F-stat	107.770	231.539	329.624	329.652	59.214
obs	122	160	179	183	183

***, **, * indicate significance at 1%, 5%, and 10%. The estimates reported in panels A and B of this table correspond to the effect of the treatment on the subindex of incentive practices controlling for log-sales per worker winsorized at 10th and 90th percentiles. In panel A, columns 1 - 5 report OLS estimates of β_1 in equation (5) including log-sales per worker as a control. In panel B, these columns report the IV estimates of β_1 in equation (6) including log-sales per worker as a control. In panel C, they report the estimates of the first stage corresponding to the IV estimates in panel B. The F-stat of that first stage is reported below panel C. The values in parentheses are standard errors clustered at the level of the firm. Estimates in columns 1, 2 and 3 use bandwidths of 10, 20, and 30 points respectively, uniform kernel, and linear polynomial. Column 4 reports similar estimates using the full sample. Column 5 reports similar estimates using the full sample and a cubic polynomial.

G Changes in recent years

G.1 Questions per category of change

In the survey, I asked whether the following changes had occurred in the firm. The possible answers were yes or no.

Changes in organizational structure:

- Some positions were eliminated.
- Some positions were created.
- Responsibilities of some positions were changed.

Changes in the workforce:

- Some position were eliminated.
- Some positions were created.
- Responsibilities of some positions were changed.

Improvement in machinery and infrastructure:

- New machines were bought.
- Business infrastructure was renewed.

Reductions in cost:

- Labor cost was reduced.
- Materials cost was reduced.
- Energy cost was reduced.

Change in customers:

- New local customer.
- New foreign customer.
- Inserted into the mining, forestry, or fishing industry.
- Started selling to the state.

Change in suppliers:

- Stopped dealing with a supplier.
- Started dealing with a new supplier.

G.2 Results for other changes

Table 26: Effect on changes in customers

	Usual inference					Randomized inference		
	bw=10	bw=20	bw=30	full	full	w=2mp	w=5	w=7.5
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. ITT estimate								
right	0.224	0.288**	0.245**	0.188	0.202	0.212	0.190	0.225
	(0.177)	(0.138)	(0.124)	(0.117)	(0.208)			
rand. inf. p-val.						0.117	0.083	0.026
B. LATE estimates								
treated	0.268	0.352**	0.290**	0.223	0.266			
	(0.211)	(0.169)	(0.148)	(0.138)	(0.275)			
C. First stage								
right	0.837***	0.819***	0.844***	0.844***	0.759***			
	(0.080)	(0.054)	(0.047)	(0.047)	(0.099)			
F-stat	108.961	232.313	329.115	329.115	58.810			
obs	122	160	179	183	183	58	96	111

***, **, * indicate significance at 1%, 5%, and 10%. The estimates reported in panels A and B of this table correspond to the effect of the treatment on a Kling et al. (2007)-type index summarizing the questions related with changes in customers (see appendix G.1 for details about these questions). In panel A, columns 1 - 5 report OLS estimates of β_1 in equation (5). In panel B, these columns report the IV estimates of β_1 in equation (6). In panel C, they report the estimates of the first stage corresponding to the IV estimates in panel B. The F-stat of that first stage is reported below panel C. The values in parenthesis are standard errors clustered at the level of the firm. Estimates in columns 1, 2 and 3 use bandwidths of 10, 20, and 30 points respectively, uniform kernel, and linear polynomial. Column 4 reports similar estimates using the full sample. Column 5 reports similar estimates using the full sample and a cubic polynomial. Columns 6 - 8 in panel A report two values. The first value is the mean difference of the dependent variable between observations located to the left and right of the cutoff. The second value is the randomized inference p-value of a test of the sharp null hypothesis that the effect of the dependent variable is zero. Estimates in column 6 uses observations within two mass points of the cutoff. Estimates in columns 7 and 8 use observations within 5 and 7.5 points of the cutoff.

Table 27: Effect on changes in suppliers

	Usual inference					Randomized inference		
	bw=10	bw=20	bw=30	full	full	w=2mp	w=5	w=7.5
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. ITT estimate								
right	0.306	0.400*	0.321	0.315*	0.485	0.339	0.234	0.299
	(0.272)	(0.205)	(0.199)	(0.180)	(0.320)			
rand. inf. p-val.						0.078	0.160	0.051
B. LATE estimates								
treated	0.365	0.488*	0.380	0.374*	0.639			
	(0.325)	(0.251)	(0.235)	(0.212)	(0.428)			
C. First stage								
right	0.837***	0.819***	0.844***	0.844***	0.759***			
	(0.080)	(0.054)	(0.047)	(0.047)	(0.099)			
F-stat	108.961	232.313	329.115	329.115	58.810			
obs	122	160	179	183	183	58	96	111

***, **, * indicate significance at 1%, 5%, and 10%. The estimates reported in panels A and B of this table correspond to the effect of the treatment on a Kling et al. (2007)-type index summarizing the questions related with changes in suppliers (see appendix G.1 for details about these questions). In panel A, columns 1 - 5 report OLS estimates of β_1 in equation (5). In panel B, these columns report the IV estimates of β_1 in equation (6). In panel C, they report the estimates of the first stage corresponding to the IV estimates in panel B. The F-stat of that first stage is reported below panel C. The values in parenthesis are standard errors clustered at the level of the firm. Estimates in columns 1, 2 and 3 use bandwidths of 10, 20, and 30 points respectively, uniform kernel, and linear polynomial. Column 4 reports similar estimates using the full sample. Column 5 reports similar estimates using the full sample and a cubic polynomial. Columns 6 - 8 in panel A report two values. The first value is the mean difference of the dependent variable between observations located to the left and right of the cutoff. The second value is the randomized inference p-value of a test of the sharp null hypothesis that the effect of the dependent variable is zero. Estimates in column 6 uses observations within two mass points of the cutoff. Estimates in columns 7 and 8 use observations within 5 and 7.5 points of the cutoff.

Table 28: Effect on changes in the workforce

	Usual inference					Randomized inference		
	bw=10	bw=20	bw=30	full	full	w=2mp	w=5	w=7.5
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. ITT estimate								
right	0.118	0.164	0.183	0.168	0.111	0.101	0.161	0.202
	(0.227)	(0.178)	(0.157)	(0.146)	(0.265)			
rand. inf. p-val.						0.590	0.284	0.145
B. LATE estimates								
treated	0.141	0.201	0.217	0.199	0.147			
	(0.269)	(0.216)	(0.185)	(0.172)	(0.347)			
C. First stage								
right	0.837***	0.819***	0.844***	0.844***	0.759***			
	(0.080)	(0.054)	(0.047)	(0.047)	(0.099)			
F-stat	108.961	232.313	329.115	329.115	58.810			
obs	122	160	179	183	183	58	96	111

***, **, * indicate significance at 1%, 5%, and 10%. The estimates reported in panels A and B of this table correspond to the effect of the treatment on a Kling et al. (2007)-type index summarizing the questions related with changes in the workforce (see appendix G.1 for details about these questions). In panel A, columns 1 - 5 report OLS estimates of β_1 in equation (5). In panel B, these columns report the IV estimates of β_1 in equation (6). In panel C, they report the estimates of the first stage corresponding to the IV estimates in panel B. The F-stat of that first stage is reported below panel C. The values in parenthesis are standard errors clustered at the level of the firm. Estimates in columns 1, 2 and 3 use bandwidths of 10, 20, and 30 points respectively, uniform kernel, and linear polynomial. Column 4 reports similar estimates using the full sample. Column 5 reports similar estimates using the full sample and a cubic polynomial. Columns 6 - 8 in panel A report two values. The first value is the mean difference of the dependent variable between observations located to the left and right of the cutoff. The second value is the randomized inference p-value of a test of the sharp null hypothesis that the effect of the dependent variable is zero. Estimates in column 6 uses observations within two mass points of the cutoff. Estimates in columns 7 and 8 use observations within 5 and 7.5 points of the cutoff.

Table 29: Effect on cost reduction

	Usual inference					Randomized inference		
	bw=10 (1)	bw=20 (2)	bw=30 (3)	full (4)	full (5)	w=2mp (6)	w=5 (7)	w=7.5 (8)
A. ITT estimate								
right	-0.053	-0.190	-0.049	-0.147	-0.218	-0.178	-0.073	-0.149
	(0.267)	(0.193)	(0.186)	(0.172)	(0.284)			
rand. inf. p-val.						0.321	0.605	0.294
B. LATE estimates								
treated	-0.064	-0.232	-0.058	-0.174	-0.287			
	(0.320)	(0.237)	(0.221)	(0.205)	(0.379)			
C. First stage								
right	0.837***	0.819***	0.844***	0.844***	0.759***			
	(0.080)	(0.054)	(0.047)	(0.047)	(0.099)			
F-stat	108.961	232.313	329.115	329.115	58.810			
obs	122	160	179	183	183	58	96	111

***, **, * indicate significance at 1%, 5%, and 10%. The estimates reported in panels A and B of this table correspond to the effect of the treatment on a Kling et al. (2007)-type index summarizing the questions related with reductions in cost (see appendix G.1 for details about these questions). In panel A, columns 1 - 5 report OLS estimates of β_1 in equation (5). In panel B, these columns report the IV estimates of β_1 in equation (6). In panel C, they report the estimates of the first stage corresponding to the IV estimates in panel B. The F-stat of that first stage is reported below panel C. The values in parenthesis are standard errors clustered at the level of the firm. Estimates in columns 1, 2 and 3 use bandwidths of 10, 20, and 30 points respectively, uniform kernel, and linear polynomial. Column 4 reports similar estimates using the full sample. Column 5 reports similar estimates using the full sample and a cubic polynomial. Columns 6 - 8 in panel A report two values. The first value is the mean difference of the dependent variable between observations located to the left and right of the cutoff. The second value is the randomized inference p-value of a test of the sharp null hypothesis that the effect of the dependent variable is zero. Estimates in column 6 uses observations within two mass points of the cutoff. Estimates in columns 7 and 8 use observations within 5 and 7.5 points of the cutoff.

Table 30: Effect on changes in organizational structure

	Usual inference					Randomized inference		
	bw=10	bw=20	bw=30	full	full	w=2mp	w=5	w=7.5
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. ITT estimate								
right	0.370*	0.368**	0.401***	0.315**	0.304	0.232	0.313	0.292
	(0.212)	(0.162)	(0.154)	(0.141)	(0.241)			
rand. inf. p-val.						0.134	0.023	0.022
B. LATE estimates								
treated	0.442*	0.449**	0.475***	0.373**	0.401			
	(0.252)	(0.196)	(0.181)	(0.165)	(0.317)			
C. First stage								
right	0.837***	0.819***	0.844***	0.844***	0.759***			
	(0.080)	(0.054)	(0.047)	(0.047)	(0.099)			
F-stat	108.961	232.313	329.115	329.115	58.810			
obs	122	160	179	183	183	58	96	111

***, **, * indicate significance at 1%, 5%, and 10%. The estimates reported in panels A and B of this table correspond to the effect of the treatment on a Kling et al. (2007)-type index summarizing the questions related with changes in the organizational structure (see appendix G.1 for details about these questions). In panel A, columns 1 - 5 report OLS estimates of β_1 in equation (5). In panel B, these columns report the IV estimates of β_1 in equation (6). In panel C, they report the estimates of the first stage corresponding to the IV estimates in panel B. The F-stat of that first stage is reported below panel C. The values in parenthesis are standard errors clustered at the level of the firm. Estimates in columns 1, 2 and 3 use bandwidths of 10, 20, and 30 points respectively, uniform kernel, and linear polynomial. Column 4 reports similar estimates using the full sample. Column 5 reports similar estimates using the full sample and a cubic polynomial. Columns 6 - 8 in panel A report two values. The first value is the mean difference of the dependent variable between observations located to the left and right of the cutoff. The second value is the randomized inference p-value of a test of the sharp null hypothesis that the effect of the dependent variable is zero. Estimates in column 6 uses observations within two mass points of the cutoff. Estimates in columns 7 and 8 use observations within 5 and 7.5 points of the cutoff.

H Exploiting complementarity under financial constraints

In the main body of the paper, I illustrated a case in which a subsidy was used to modify the incentives of a firm. In this subsection, I show how a subsidy can be used to unleash a technological upgrading process desired by the firm, but obstructed by the presence of financial constraints. To be more specific, I study a case in which the unrestricted optimal action is to adopt t_1 and t_2, but financial constraints impede these actions. I introduce financial frictions in the model by imposing the restriction that the firm cannot spend more than R in technology adoption in any given period. A lower value of R represents a tighter financial restriction[14]. If R is small enough, the firm would not be able to afford the adoption cost of technology t_1, $(\phi_{t_1} - 1)^2$, in any period and would keep t_0 until production time.

First, let's describe the set of possible value of possible values of (ϕ_{t_1}, ϕ_{t_2}) that would make adopting t_1 and t_2 the optimal action path in the absence of financial constraints. This baseline situation would occur if conditions (7) and (8) hold.

$$\phi_{t_2} b - (\phi_{t_2} - \phi_{t_1})^2 - (\phi_{t_1} - 1)^2 > \phi_{t_1} b - (\phi_{t_1} - 1)^2 \tag{7}$$

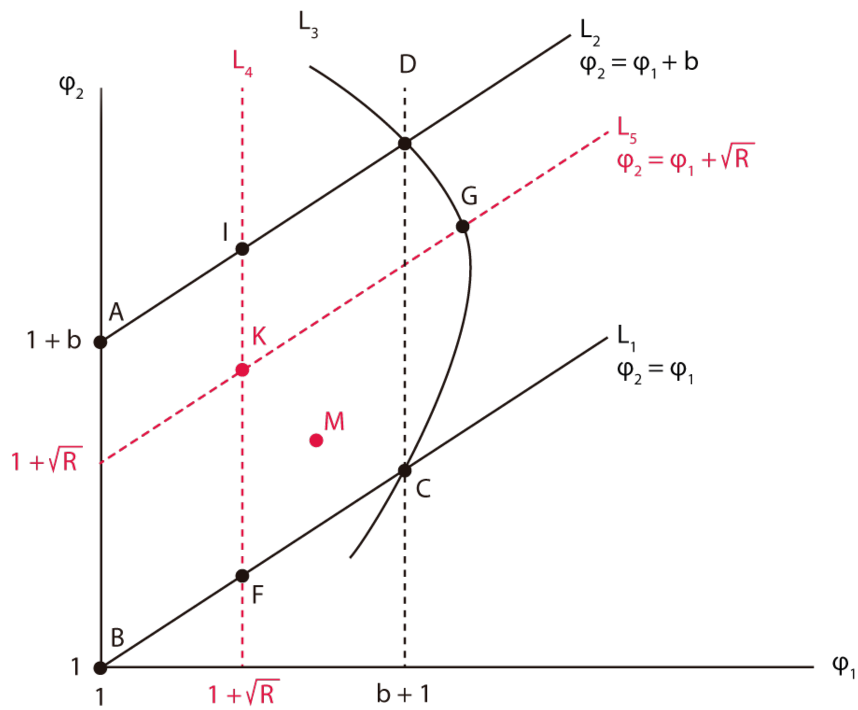
$$\phi_{t_2} b - (\phi_{t_2} - \phi_{t_1})^2 - (\phi_{t_1} - 1)^2 > b \tag{8}$$

Condition (7) ensures that, if t_1 is reached, the firm will want to continue upgrading to t_2. Condition (8) guarantees that the option of upgrading to t_1 and then to t_2 is better than simply keeping t_0 [15]. Figure 9 represents graphically these conditions in a (ϕ_{t_1}, ϕ_{t_2})-plane. They are satisfied in the area ABCGD. Condition (7) is satisfied between the two parallel lines L1 and L2, and condition (8) holds to the left of the curve L3. (ϕ_{t_1}, ϕ_{t_2}) cannot be below L2 because technological downgrading is never optimal. If (ϕ_{t_1}, ϕ_{t_2}) were above L1 and to the left of L3, the firm would upgrade to t_1 in either the first or second period, but would not continue to t_2. If (ϕ_{t_1}, ϕ_{t_2}) were to the right of L3, reaching t_1 from the initial t_0 would be too costly, and the firm would just keep t_0 until production time.

[14] Note that the financial restriction applies to expenses in technology adoption, but not to the purchase of inputs. This is reasonable as inputs can be financed with credit lines for working capital, which are easier to access than credit for technology adoption. A similar assumption is made in the baseline model presented in Manova (2012), in which the credit constraint affects the payment of the export fixed costs, but not the purchase of inputs.

[15] When writing condition (8), I have assumed that the optimal action in lower node of the second period in figure 1 is keeping t_0. Another possibility would be that upgrading to t_2 were optimal in that node. In that case condition (8) would need to be substituted with $\phi_{t_1} b - (\phi_{t_1} - 1)^2 > b$. Under condition (7), this implies condition (8). The analysis here focuses on the more general case.

Figure 9: Possible parameter configurations



Second, let's introduce financial constraints. This means putting a restriction to the sequence of technologies that are possible for the firm. In particular, if the firm cannot spend more that R in any given period; then it would not be able to adopt any technology with productivity higher than $1 + \sqrt{R}$ in the first period, restriction represented with the line L4. Similarly, given a first period technology with productivity ϕ_{t_1}; the firm would not be able to reach any technology beyond $\phi_{t_2} = \phi_{t_1} + \sqrt{R}$, restriction represented by L5.

Consider a situation in which the parameters $\phi_{t_1} and \phi_{t_2}$ are as in point M. In this case, the unrestricted optimal action path of the firm would be to adopt t_1 and then t_2; but due to the financial constraint, that would not be possible as the firm would not be able to upgrade to t_1 in the first period. A subsidy for projects to upgrade to t_1 in the first period would move the restriction L4 to the right up to the point in which upgrading to t_1 becomes feasible. With this support the firm would adopt t_1 and then it would upgrade to t_2 without additional subsidy. This second upgrade is possible without additional support because technology t_2 is close to t_1 (M is below L5 in figure 9), hence the financial constraint would not be able to prevent the adoption of t_2 once t_1 has been reached. This policy action would be welfare improving because, with the subsidy, the firm would get $\phi_{t_2} b - (\phi_{t_2} - \phi_{t_1})^2 - (\phi_{t_1} - 1)^2 + S$ instead of b. Because $\phi_{t_2} b - (\phi_{t_2} - \phi_{t_1})^2 - (\phi_{t_1} - 1)^2 > b$ by assumption, the firm would be able to pay back the subsidy if required, and still be better off.

I Proof of supermodularity

Let's call T_1 and T_1' to two possible values for the technology adopted in the first period such that $(\phi_{T_1'} > \phi_{T_1})$. Similarly T_2 and T_2' are two possible values of the technology in the second period $(\phi_{T_2'} > \phi_{T_2})$. In this case, supermodularity of the profit function means that:

$$\pi(\phi_{T_1'}, \phi_{T_2'}) - \pi(\phi_{T_1'}, \phi_{T_2'}) > \pi(\phi_{T_1}, \phi_{T_2'}) - \pi(\phi_{T_1}, \phi_{T_2}) \iff$$

$$\phi_{T_2'} b - (\phi_{T_2'} - \phi_{T_1'})^2 - \phi_{T_2} b + (\phi_{T_2} - \phi_{T_1'})^2 > \phi_{T_2'} b - (\phi_{T_2'} - \phi_{T_1})^2 - \phi_{T_2} b + (\phi_{T_2} - \phi_{T_1})^2 \iff$$

$$-(\phi_{T_2'}^2 - 2\phi_{T_2'}\phi_{T_1'} + \phi_{T_1'}^2) + (\phi_{T_2}^2 - 2\phi_{T_1'}\phi_{T_2} + \phi_{T_1'}) > -(\phi_{T_2'}^2 - 2\phi_{T_1}\phi_{T_2'} + \phi_{T_1}^2) + (\phi_{T_2}^2 - 2\phi_{T_1}\phi_{T_2} + \phi_{T_1}^2) \iff$$

$$2\phi_{T_2'}\phi_{T_1'} - 2\phi_{T_1'}\phi_{T_2} > 2\phi_{T_1}\phi_{T_2'} - 2\phi_{T_1}\phi_{T_2} \iff$$

$$2\phi_{T_2'}(\phi_{T_1'} - \phi_{T_1}) - 2\phi_{T_2}(\phi_{T_1'} - \phi_{T_1}) > 0$$

and the last conditions is true because $\phi_{T_1'} > \phi_{T_1}$ and $\phi_{T_2'} > \phi_{T_2}$.