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Inter-American Development Bank
Institutions for Development Sector
Innovation in Citizen Services Division

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KNOWLEDGE FOR RESULTS

and the Efficiency of Public Agencies in Colombia

IDB

Knowledge for Results and the Efficiency of Public Agencies in Colombia*

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February 2022

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Contents

Abstract

This paper documents the effects of an intervention on knowledge sharing, in which information embedded in efficient private organizations is used to improve bureaucratic procedures of public agencies. In particular, it analyzes the impact of the Knowledge for Results (K4R) program on the efficiency of public agencies in Colombia. The findings of the study indicate that K4R is associated with a statistically significant improvement in operational efficiency. The paper presents two examples of K4R. In the first example, K4R reduced the time that local ombudsman offices need to deal with incoming petitions from citizens. In the second example, K4R reduced the time that oncology patients spend in an emergency clinic until they are discharged from the hospital. These time reductions are quantitatively relevant and imply efficiency gains of between 25 and 40 percent relative to pre-program levels.

JEL codes: H43, H75

Keywords: new public management, knowledge management, policy evaluation.

Introduction

1

Introduction

Economists, political scientists, and sociologists have long emphasized the importance of the quality of the bureaucracy for an efficient functioning of the state (e.g., Downs, 1964; Evans and Rauch, 1999; Finan, Olken, and Pande, 2015; Weber, 1904–1911;). This paper documents a study of an intervention that aims to improve the quality of state bureaucracy. In particular, it provides non-experimental evidence on the impact of the Knowledge for Results (K4R) program on the efficiency of local public agencies in Colombia. K4R uses information embedded in efficient private organizations to improve bureaucratic procedures of public agencies. The findings indicate that K4R is associated with a significant improvement in operational efficiency of local public agencies.

We present two examples of the intervention. The first example involves local ombudsman's offices, which investigate complaints leveled against businesses and other organizations, including the government. In this case, we find that K4R is associated with a statistically significant reduction in the time that public service teams process citizens' petitions. The analysis implies that offices reduced time management by approximately 40 percent relative to pre-program levels. The second example involves an oncology clinic that provides health care to patients in need of urgent treatments. In this case, our findings indicate that implementation of K4R is associated with a statistically significant reduction in the number of days patients spend in the clinic before being discharged. The observed reduction is approximately 25 percent relative to pre-program levels.

Our paper is closely related to Bloom et al. (2013), who study how management practices can affect firm productivity. Our paper differs from theirs in two key aspects. First, their intervention shows how an improvement in managerial quality (e.g., more efficient management of inventories) can increase private sector profitability. Our contribution is to broaden this concept by showing that management practices also matter in explaining the quality of state bureaucracy. Second, the intervention in Bloom et al. (2013) consists of applying a range of standard manufacturing principles set up by a team of management consultants. Our intervention represents an ad hoc adjustment of public entities' internal processes shaped by the expertise of the collaborating institutions. Thus, our work emphasizes cross-organizational dissemination of knowledge. This has profound implications for intervention costs and scalability. Indeed, the low cost of our intervention, combined with strong effects on efficiency, leads to a high return per dollar invested.

This has profound implications for intervention costs and scalability. Indeed, the low cost of our intervention, combined with strong effects on efficiency, leads to a high return per dollar invested.

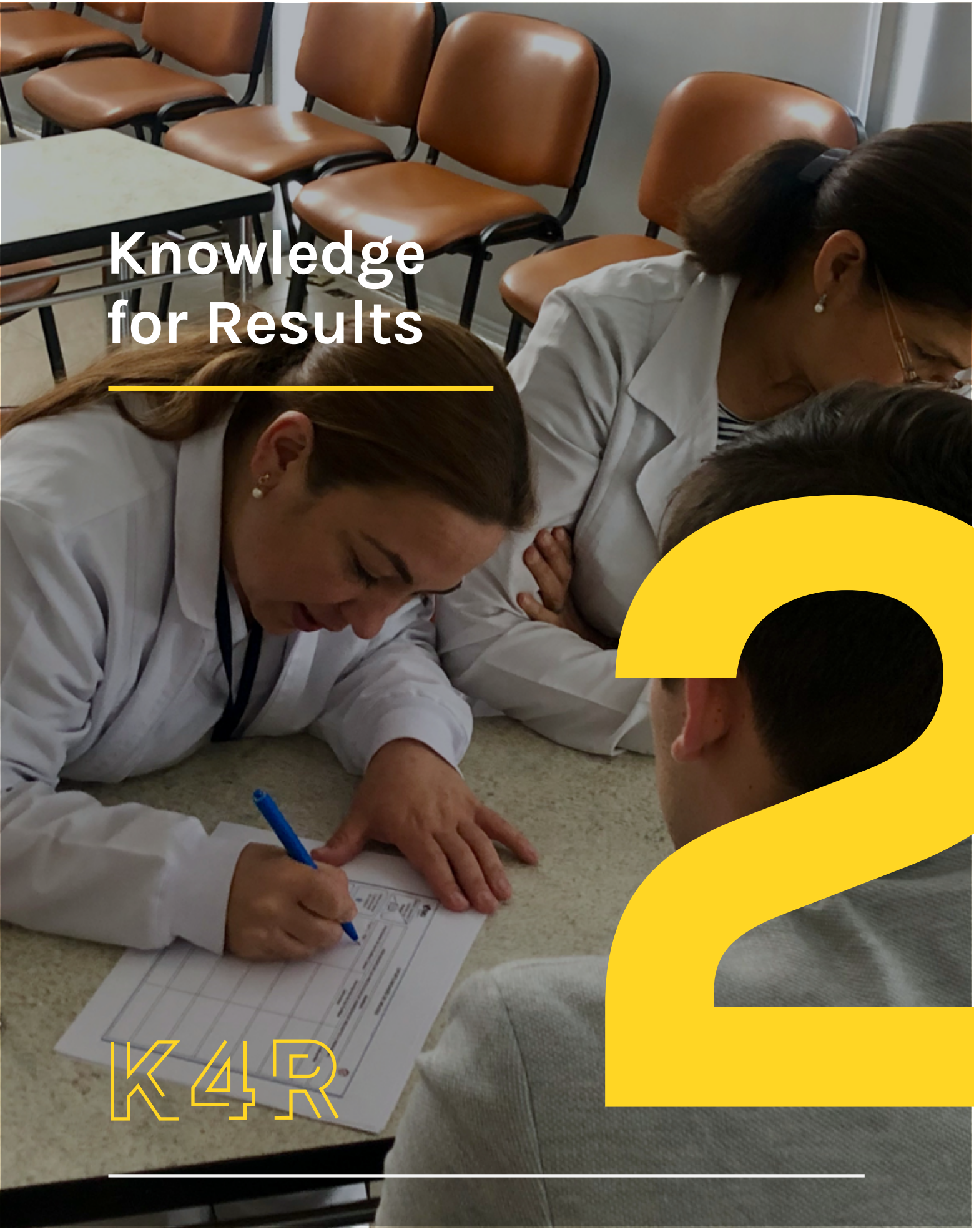
Our paper also relates to a public administration literature that emphasizes the study of factors that lead to greater efficiency in public services, particularly within the framework of New Public Management, or NPM (Gruening, 2001). NPM consists of the adoption of organizational forms and management techniques from the private sector. The NPM literature is extensive and covers many topics, such as public–private partnerships, accountability, performance management, decentralization, contracting out, e-government, and collaborative networks. Empirical evidence on the link between NPM and government efficiency includes research by Alonso, Clifton, and Díaz-Fuentes (2015), Andrews and Entwistle (2015), Andrews and Van de Walle (2013), and Pérez-López, Prior, and Zafra (2015). Andrews and Van de Walle (2013) studied the relationship between NPM practices and citizens' perceptions of service

efficiency, responsiveness, equity, and effectiveness in English local governments. They find that public–private relationships have a negative relationship with citizens' perceptions of all four dimensions of local service performance, but an entrepreneurial strategic orientation exhibits a positive association with all four. Pérez-López, Prior, and Zafra (2015) examine the effect of several NPM practices (creation of agencies, contracting out, inter-municipal cooperation, mixed firms) on the overall efficiency of Spanish local governments during the global recession. Their main finding is that the adoption of mixed firms contributes to higher levels of cost efficiency, and thus it may be a suitable instrument in periods of crisis. Alonso, Clifton, and Díaz-Fuentes (2015) do not find evidence that NPM in Madrid hospitals makes them more efficient than traditionally managed ones. Andrews and Entwistle (2015) find that only local governments in England with very strong management capacity are able to realize productive efficiency gains from public–private partnership. Our contribution to this literature is to exploit quasi-experimental approaches to identify the causal impact of NPM practices (streamlining public institutions' procedures with public–private cooperation) on the quality of the state bureaucracy.

Finally, our work also ties in with the literature on Knowledge Management (KM). KM consists of a set of strategies that use knowledge to improve the connection between people and technology to leverage knowledge within an organization (Omotayo, 2015). KM has been proposed as a key driver for increasing performance (Bousa and Venkitachalam, 2013; Earl, 2001; Kamhawi, 2012). One of KM's main areas of interest is knowledge sharing (Lee and Choi, 2003; Quigley et al., 2007). In a seminal study, Schermerhorn (1977) finds a positive relationship between inter-organizational information-sharing activities and perceived task accomplishment within the organization. More recent studies stress that knowledge sharing can be challenging and depends on several factors. Amayah (2013) examines sharing in public organizations using a questionnaire design and finds that community-related considerations are strongly associated with more sharing, and that others factors can either contribute to (e.g., normative considerations and empathy) or mitigate (e.g., the presence of potential private benefits) sharing. Quigley et al. (2007) studied the exchange of information between partners using computer-based interactive management decision-making simulations, where participants assumed the role of manager for a private organizational unit. The study finds that sharing can be motivated by providing economic incentives to group performance, which in turn has a positive effect on individual performance. In general, the literature tends to be more concerned with knowledge being used to gain a competitive advantage within the organization.

Our paper provides an example of knowledge sharing between organizations. To the best of our knowledge, ours is the first paper that evaluates the impact of knowledge-sharing mechanisms between organizations (with examples of both public–public and private–public sharing) on reducing red tape in the public sector.

The paper is organized as follows: Section 2 describes the K4R methodology. Section 3 presents the case of the Ombudsman office. Section 4 presents the case of the oncology clinic. Section 5 concludes.



Knowledge for Results

2

K4R

Knowledge for Results

Since 2012, the Inter-American Development Bank (IDB) has been developing a methodology called Knowledge for Results (K4R). This methodology aims to help public institutions in Latin America and the Caribbean improve their performance while streamlining their processes and procedures by using available knowledge in the public or private sector. Interventions within this methodology consist of designing management tools, adaptable to the specific needs of a wide array of organizations, that can be implemented with minimal monetary investments, so that the public sector can optimize its bureaucratic procedures.[1]

K4R embeds NPM and KM theoretical frameworks by streamlining processes and procedures of public institutions by developing public–private solutions at minimal cost using available resources (value for money). First, it conducts an analysis focused on the factors that affect the efficiency, quality, and/or effectiveness of such procedures and/or processes. Second, it mobilizes, exchanges, and uses the knowledge existing in public (state institutions), private (firms), and/or third sector organizations (universities, non-governmental organizations, communications media, etc.), adapted to the context of the targeted public institution.

K4R is developed in six stages: (i) scope, (ii) assessment, (iii) knowledge exchange, (iv) design thinking, (v) piloting and measuring, and (vi) implementing successful solutions (See appendix).

STAGE 1: Scope

The first stage (scope) consists of preparing the institutional conditions for developing an intervention, beginning with a planning and management exercise at the strategic, managerial, and operational levels.

STAGE 2: Assessment

The second stage (assessment) consists of elaborating an institutional assessment based on a characterization of the business model (that is, how the organization is set up to generate value) and mining data to determine the state of the selected process and analyze the changes or adjustments that need to be implemented. The IDB leads this exercise with the guidance of the highest-level authorities and support from the management team, but the officials involved in the day-to-day management of the process participate actively in identifying the main bottlenecks, the problems that affect process operation, and the opportunities for improvement to resolve them, using their knowledge and experience to the fullest.

STAGE 3: Knowledge Exchange

The third stage (knowledge exchange) consists of identifying public or private oganizations that have achieved expertise with consolidated models or

1 For more details about the methodology, see Arisi et al. (2020).

K4R is developed in six stages: (i) scope, (ii) diagnose, (iii) knowledge exchange, (iv) design thinking, (v) piloting and measuring, and (vi) implementing successful solutions.

practices that can be transferred and adapted to the beneficiary institution. The IDB sets the alliances and facilitates knowledge exchange sessions that include benchmarking or ad hoc advisory for problem solving.

STAGE 4: Design Thinking

The fourth stage (design thinking) consist of inventing a creative design process to experiment and create solutions and/or tools capable of achieving the desired outcomes. To this end, it makes use of the know-how and knowledge of civil servants with respect to their own institution, its dynamics, and arrangements, as well as the knowledge acquired throughout the entire experimentation process. The solutions follow an operating model scheme that ensures logical and operational consistency, thereby helping to improve the process according to the challenge set.

STAGE 5: Piloting and Measuring

The fifth stage (piloting and measuring) consist of conducting a pilot project to check whether they are effective or need adjustment. This experimentation process is fundamental to organizational analysis and decision making. A trial-and-error approach does not cause frustration, but rather opens up opportunities and naturally encourages officials to make the project a success. This stage includes monitoring, practice review, and adjustments (if necessary), and a closure of the test project which includes results, lessons learned, and conclusions.

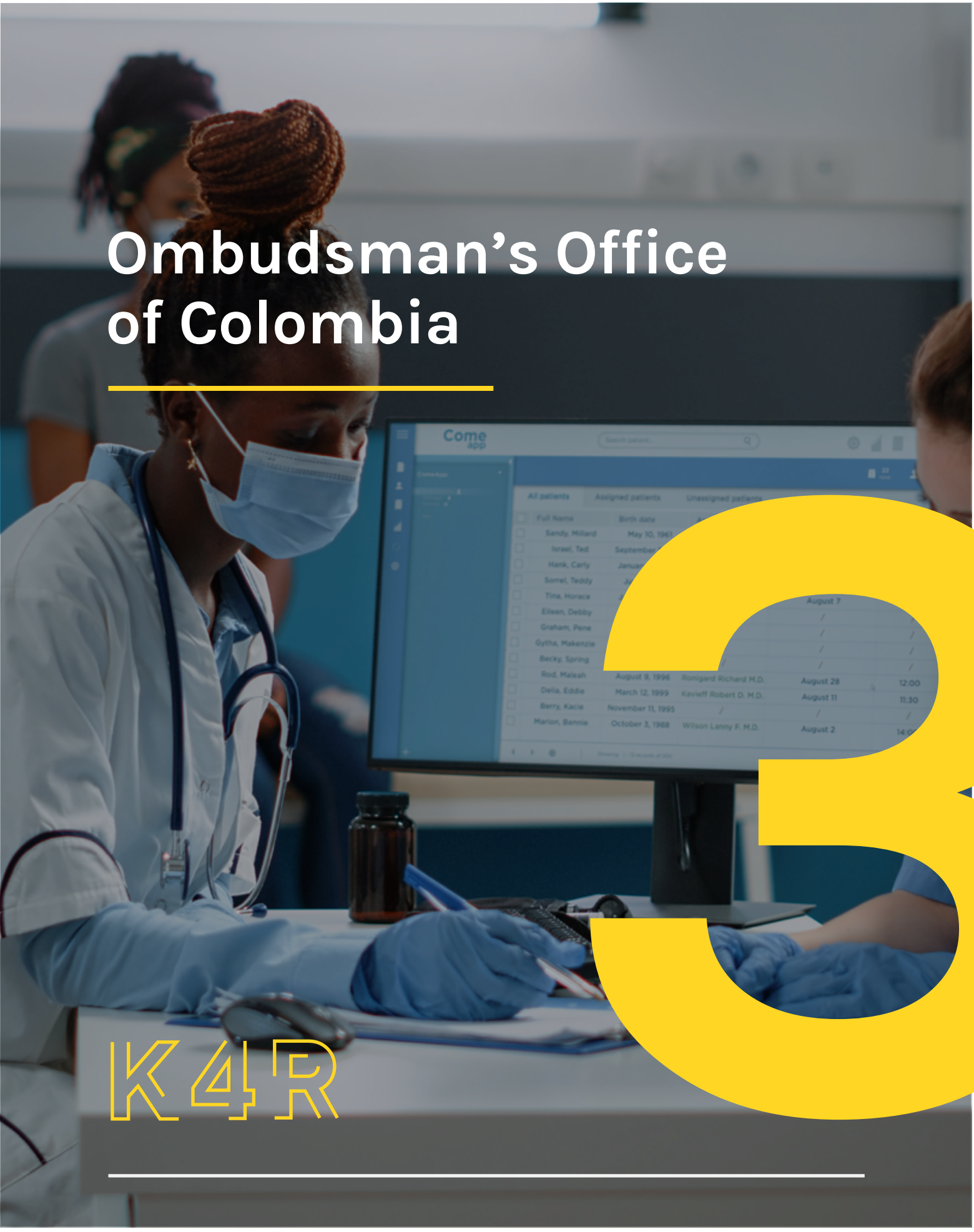
STAGE 6: Implementing Successful Solutions

The final stage (implementing successful solutions), consists of carrying out activities to ensure the implementation, sustainability, and internal and external communication of the intervention. It has two main aims: (i) for the institution to officially adopt the solution created by the team and incorporate it into its day-to-day operations and (ii) for the institution to have a longer-term road map that can be used for future planning and/or institutional transformation processes.

The underlying idea is that organizations share a common DNA. That is, what is done in one organization can be adapted to different environments regardless of the nature of the organization—public, private, and/or third sector. In this context, benchmarking is the basis of the management tools design process developed by K4R.

In Section 3, we evaluate the impact of K4R on the efficiency of the Ombudsman's Office in dealing with citizens petitions. In Section 4, we evaluate the impact of K4R on the efficiency of an oncology clinic in providing health care to incoming patients.

Ombudsman's Office of Colombia



K4R

Ombudsman's Office of Colombia

The Ombudsman's Office of Colombia is responsible for overseeing compliance with human rights laws and enabling people to access justice services. It mainly operates on demand: citizens with complaints or in need of counsel regarding access to and quality of public services can request assistance from the Ombudsman's Office, the entity responsible for collecting and consolidating petitions in the country. The Ombudsman's Office classifies all the petitions before sending them to the corresponding regional offices, based on the location of the petitioner, for analysis and technical response.[2] There are 38 regional offices in Colombia, each of which has has one team for each type of petition (e.g., the health team in the Bogota office manages all petitions regarding health in that city).

In accordance with federal law, regional offices must process petitions in less than 15 days, but this target is not met in practice. In our sample, the average processing time before the intervention is 89 days.

The Ombudsman has a basic procedure for processing petitions, which consists of three stages: (i) reception and registration of the petition; (ii) transfer of the petition to the regional office and the central topic area (*Delegada*); and (iii) response to the petition. To account for the delay, the K4R program assessed the petitions management process and identified and prioritized five main issues that affected the untimely response to citizens: (i) the lack of prioritization criteria; (ii) poor quality checks to avoid repetition of requests; (iii) extensive use of hardcopy communications; (iv) excessive number of steps to validate and send answers to the petitioners; and (v) lack of standardized protocols for coordinating and managing responses between the central office and the regional offices.

The aim of the intervention was to reduce response time in the regional offices. It focused on complaints related to health services provided by the public sector. Health teams at targeted offices adopted a new management system designed in collaboration with the National Instutite of Surveillance of Medicines and Food (Instituto Nacional de Vigilancia de Medicamentos y Alimentos, or INVIMA),[3] a local public entity awarded for the quality its customer service, and EPS-SURA, a private firm known for being one of the best health care providers in Colombia.[4]

The intervention employs a new model for the management of petitions, which includes: (i) prioritization criteria for internally managing petitions and responses; (ii) a new protocol for the management process, which includes a road map, roles, and time frames; (iii) the designation of a technical advisory group of public servants in the regional offices responsible for responding to the petitions; (iv) standardized answer sheets shared via email and digital signatures; and (v) a regional (*Delegada*) governance model in which regional officials can provide guidance to the central office (Bogota) and support the management of the regional offices. The intervention suggests adjustments to the internal proceses of the Ombudsman's Office, shaped by the expertise of the collaborating institutions that helped redesign the system to respond to all health-related petitions.

There are 38 public regional offices in Colombia, with one specialized team per office that deals with health-related petitions. The intervention targeted health teams of regional offices participating in the program and was

2 The Ombudsman's Office has established 12 categories of human rights. It has central offices in Bogota called *Defensorías Delegadas*, which provide services in these areas.

3 INVIMA shared with officials from the Ombudsman's Office how it establishes key performance indicators (KPIs), a successful practice for improving petition management process.

4 EPS-SURA shared its user-oriented petitions management model. This model consider filters and special criteria for processing, prioritizing, and managing requirements of petitioners according to the complexity of the complaint.

implemented in two phases. The first phase began on November 1, 2017, in the regional offices of Bogota and Cundinamarca, where the implementation of the new management system started. The second phase began on July 1, 2019, in four new offices (Amazonas, Arauca, Cauca, and La Guajira). That is, the intervention has 6 treated offices, and there are 32 control offices.

DATA

The sample includes monthly data on health-related petitions received by regional offices (Ombudsman) in Colombia during the three-year period from January 1, 2017, to December 31, 2019 (1,095 days). Regional offices in Colombia received around 71,000 petitions during the period under review. These petitions include complaints (such as "poor or late medical care"), petitions for council requests, or other petitions, such as access to documents or services.

Table 1 presents summary statistics of the data. We have monthly data of targeted offices. The intervention variable is Treatment, a dummy that takes the value 1 for treated regional offices (an office participating in the program during that month).

The outcome variable is Duration, which aims to capture the efficiency of the health team. Duration is the monthly average of petition time, that is, the number of days that elapsed between the time a petition was received and the time it was resolved. For petitions resolved in less than 24 hours, petition time takes the value 1; for petitions resolved between 24 and 48 hours, petition time takes the value 2, and so on. For petitions that were not resolved within our sample period, petition time is calculated as if the petition were resolved on the last day of the sample.[5]

Finally, our sample includes data on the petition type according to the three categories presented earlier (complaints, council requests, and access to documents and services). Since the time needed to address a given petition can vary with its type, the monthly share of each petition type will be used to control for potential heterogeneity between treated and control offices regarding the evolution of petitions' share composition.

5 For example, for a petition received on March 1, 2019, that was not resolved within our sample period, petition time equals 305, which is the number of days elapsed from reception date to the last day of our sample, December 31, 2019. All results remain the same if we restrict the sample only to consider petitions that were resolved within our sample period (results not shown).

Table 1. Summary Statistics: Ombudsman's Office

	Observations	Mean	Standard deviation	Minimum	Maximum
Treatment	1,327	0.054	0.227	0	1
Duration	1,327	108.028	105.913	1	985
Share of complaints	1,327	0.528	0.292	0	1
Share of council requests	1,327	0.178	0.232	0	1

Notes: The sample includes average monthly data on health-related petitions received by public regional offices (ombudsman) in Colombia from January 1, 2017 to December 31, 2019 (38 offices and 36 months, although there are 41 observations missing that account for 5 offices that did not received petitions during some months). Treatment takes the value 1 for treated regional offices (an office participating in the program during that month). Duration is the monthly average of the number of days that elapsed between the time when petitions were received and when they were resolved.

ECONOMETRIC METHODS AND RESULTS

We want to estimate the causal impact of K4R on the office health's team efficiency. Since the treatment was not assigned to offices in an experimental way, we estimate a difference-in-differences specification that exploits the variability in the treatment status over time and regional offices. Formally, we estimate the following regression:

$$Y_{jt} = \beta\, Treatment_{jt} + \alpha_j + \mu_t + \varepsilon_{jt} \qquad (1)$$

where Y_{jt} is Duration of office j in month t, $Treatment_{jt}$ is the intervention variable, α_j is an office fixed effect, μ_t is a month fixed effect, and ε_{jt} is an error term. All standard errors are clustered at the office level. Given that there are few (six) treated clusters, we also report p-values obtained from wild bootstrap inference using the *boottest* command in Stata (Roodman et al., 2019).[6] In some specifications, we control for the share of petitions that were complaints and the share that were council requests.

In a difference-in-differences specification, the identifying assumption is that the evolution of the

6 Results remain similar when we (i) cluster erros by office or by office and month and (ii) use unrestricted estimates in the bootstrap data generating process (WCU) or impose a null hypothesis (WCR).

outcome of untreated offices is an unbiased estimator of the evolution that the outcome of treated offices would have had in the absence of the intervention (parallel-trend assumption). We first check if the parallel-trend assumption holds by testing if outcomes in the pre-treatment period evolved in a similar way between (eventually) treated and control offices. Formally, we estimate the following equation:

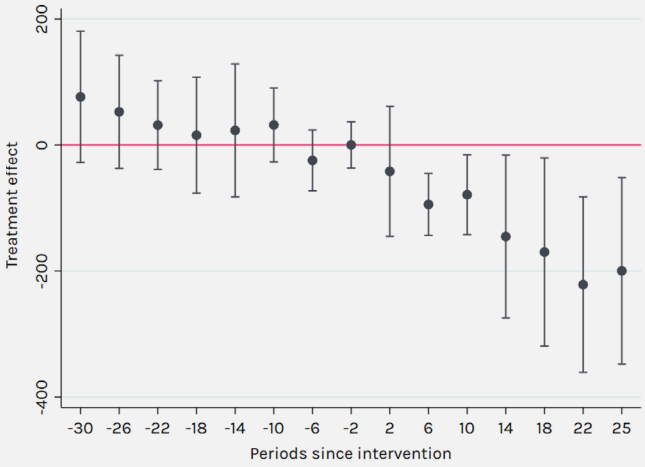
$$Y_{jt} = \sum_{q-}^{q+} \beta^k Treatment_{jt}^k + \alpha_j + \mu_t + \varepsilon_{jt} \qquad (2)$$

where $Treatment_{jt}^k$ is a dummy variable that takes the value 1 if treatment took place k periods (months) ago, q- is the pre-period furthest back (since treatment), and q+ is the post-period furthest after (since treatment) in our sample period. In this way, β^k measures the effect k periods after treatment took place. If k is negative then it measures the effect k periods before the treatment. This model captures the difference between (eventually) treated and control groups in each period.

> ***Our empirical findings support the idea that K4R is associated with a sizeable and statistically significant reduction in the time that public service teams need to deal with incoming petitions.***

Figure 1 plots the sequence of β^k (for all possible k and using one period before the treatment as the omitted dummy) and their 90 percent confidence bands. The plot shows that there are no significant differences in the evolution of the outcome variable between eventually treated and control offices before the intervention, thus providing support to our identification strategy. It also shows a significant and gradual reduction in the time that treated regional offices needed to resolve the petitions (only) after the intervention.[7]

Figure 1. Treatment Leads and Lags: Ombudsman's Office



Notes: The base dummy in the regression corresponds to the period immediately before treatment begins, represented by the period -1. Confidence intervals are at 90 percent. Standard errors are clustered at the regional office level.

Columns (1) and (2) in Table 2 report estimates for the model in levels, without and with controls. The estimated coefficients are negative and statistically significant, indicating an average reduction of between 73 and 83 days for treated offices. Columns (3) and (4) report estimates for the model in logs and show a reduction of between 40 and 35 percent in the average time needed to resolve petitions.

7 The SUTVA assumption in this setting implies that the intervention did not affect untreated offices' teams. This assumption is likely to hold, since offices do not share health teams.

Table 2. Main Results: Ombudsman's Office

	Dependent variable: Duration		Standard deviation: ln(Duration)	
	(1)	(2)	(3)	(4)
Treatment	-82.74**	-73.44**	-0.517**	-0.424*
	(39.56)	(31.81)	(0.224)	(0.224)
	[0.09]	[0.07]	[0.07]	[0.06]
Type of petition	No	Yes	No	Yes
Office fixed effects	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes
Observations	1,327	1,327	1,327	1,327
R-squared	0.607	0.662	0.650	0.719

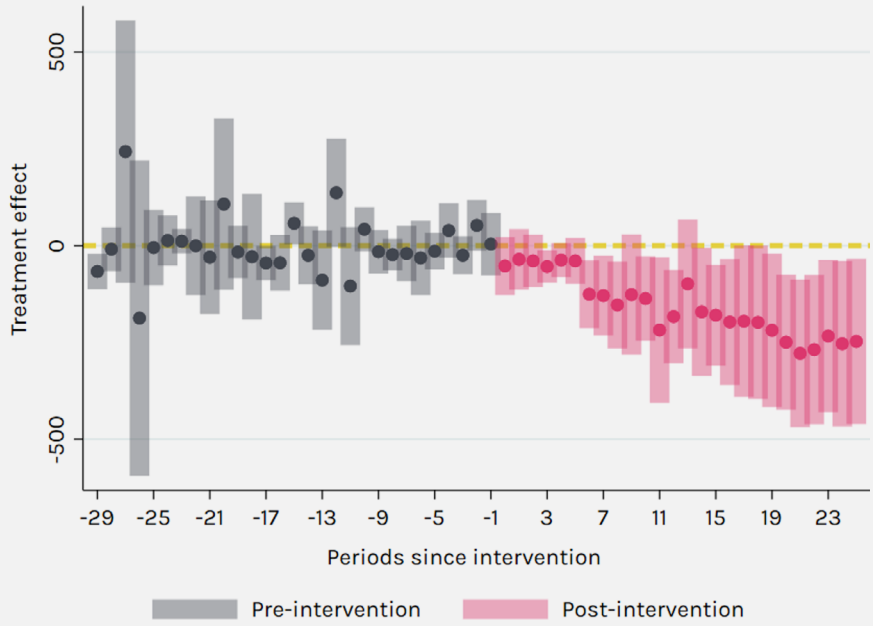
Notes: All regressions include office fixed effects (38 offices) and month fixed effects (36 months). Type of petition includes two controls: the share of petitions that were complaints and the share of petitions that were council requests in a given month. Standard errors clustered at the regional office level are in parentheses and p-values from wild bootstrap inference (999,999 repetitions) are in brackets. *Significant at the 10% level. **Significant at the 5% level.

Our empirical findings support the idea that K4R is associated with a sizeable and statistically significant reduction in the time that public service teams need to deal with incoming petitions. Our specification includes units that are treated in different time periods. This may lead to a biased estimation of the parameter of interest in the presence of time-varying effects (Goodman-Bacon, 2021). To address this concern, we compute group-time average treatment effects as proposed in Callaway and Sant'anna's (2021) framework developed for difference-in-differences setups where adoption is staggered (once treated, always treated), as these estimates do not require the assumption that the treatment effect remains constant over time.

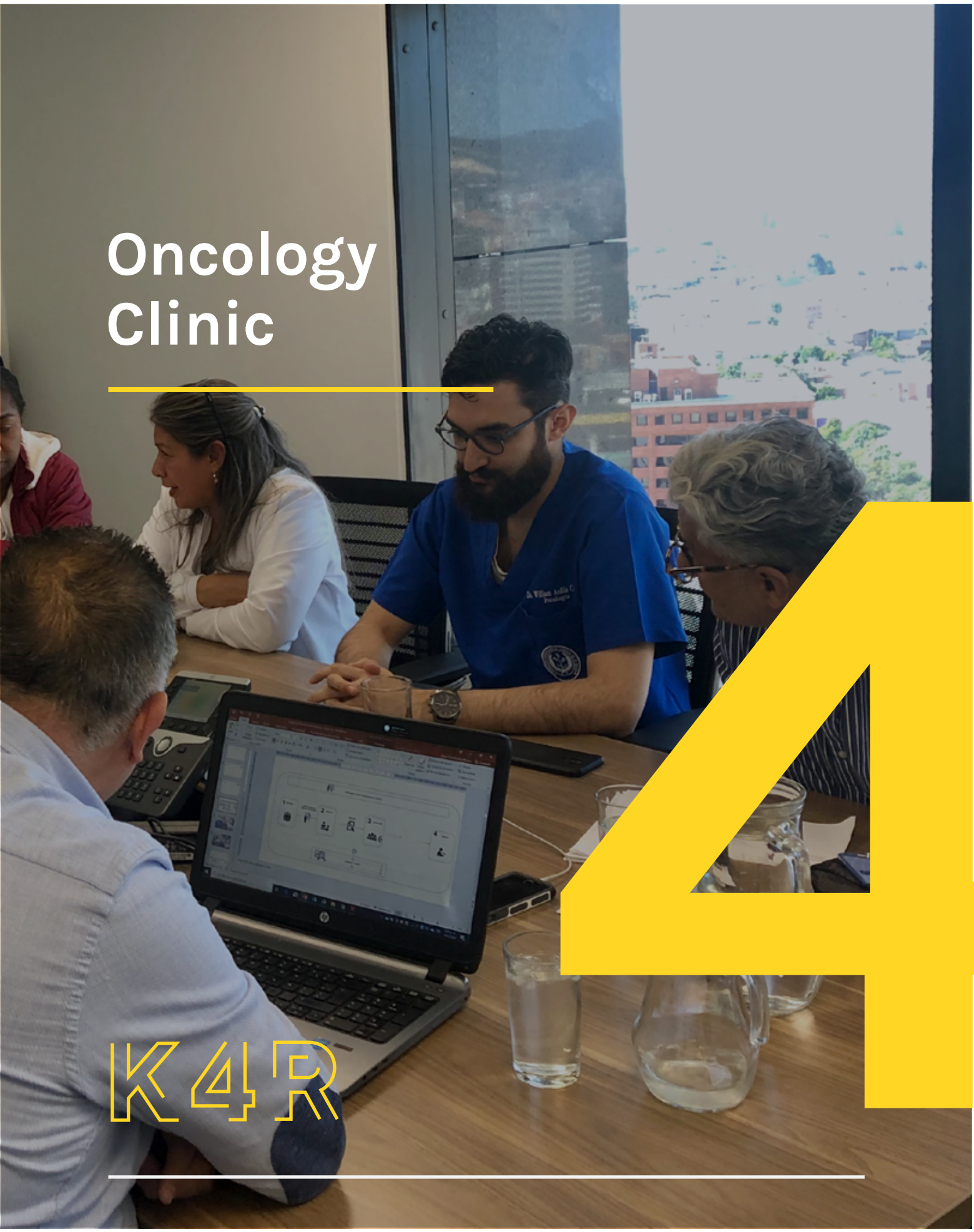
Figure 2 shows point estimates of these effects by length of exposure. The figure confirms our previous results, as it resembles the evolution of the treatment leads and lags previously reported in Figure 1. Furthermore, the estimate for the overall average treatment effect is a reduction of 77 days, in line with the results presented in Table 2.[8]

8 The overall ATT estimate is the average across groups of the time-average treatment effect for each group.

Figure 2. Average Effect by Length of Exposure: Ombudsman's Office



Notes: Each dot is the ATT in time t averaged by treatment groups, where t goes from -29 (29 months before the intervention) to +25 (25 months after the intervention). The control group is comprised of never-treated units. The first month of intervention is represented by t = 0. Confidence intervals are at 95 percent. Standard errors are clustered at the regional office level.


Oncology
Clinic
4
K4R

Oncology clinic

We now investigate the impact of K4R on the efficiency of the National Cancer Institute (Instituto Nacional de Cancerología, or INC), an oncology clinic.

> ***This consultation focuses on an early medical resolution (diagnosis) to initiate treatment as soon as possible by assigning the patient to a specialist.***

The INC is a public entity based in Bogota, Colombia, that provides health care services to cancer patients. Each year, it receives around 1,200 patients from all over the country. When patients arrive at the clinic, they first must go through administrative procedures (i.e., registration of their medical history). Next, a nurse classifies the patients according to their needs and the available medical resources at the clinic to begin the treatments. Then, patients have a consultation with a general practitioner. This consultation focuses on an early medical resolution (diagnosis) to initiate treatment as soon as possible by assigning the patient to a specialist. Then, the specialist physician determines whether the patient needs to be hospitalized and defines the course of treatment. In this case, the patient enters the emergency services and is admitted to the hospital as soon as there is a vacancy. The time that patients must wait between steps and the overall time that they spend in the clinic including hospitalization depend on the operational capacity and efficiency of the clinic. Assessments of the clinic's operational capacity within the framework of the K4R program identified several aspects affecting the amount of time that it takes to be seen by a doctor, such as poor filtering of people that do not need the service, difficulties in tracking patients, and lack of coordination between each phase of the visit.

The aim of the intervention is to reduce the total amount of time that the patient spends in the clinic by improving patient management during the visit. Based on the diagnosis, an expert team in knowledge management and benchmarking industries from the IDB identified two Colombian institutions whose experiences in emergency management could provide solutions to the National Cancer Institute: the Colombian Civil Aviation Authority and the National University of Colombia (UNAL).[9]

It consisted of adapting knowledge and best practices from the Civil Aviation Authority, the public agency that oversees the country's aviation industry, with the help of UNAL, one of the most prominent public universities in the country. The relevance of the aviation industry relates to the fact that organizations within this industry have expertise in logistics management in high-demand settings and within tight schedules. Some features of their expertise are not specific to flight, but rather on general guidelines for efficient operation of complex systems.

The intervention focused on three critical points of the process. The first is the improvement of protocols in patient admittance to the emergency unit. In this step, a specialized nurse and an administrative clerk were assigned to the waiting room to help patients navigate their care path. Each case is evaluated, prioritized, and, if it presents a life-threatening risk, immediately enters a special route. This made it possible to classify emergencies and avoid diverting urgent resources to patients who do not require immediate attention.

9 The team of experts identifies the sources of knowledge that can be used, based on the challenge (what, how, where, and why). Here, the IDB plays two essential roles: it identifies and selects the public or private organizations, either within or outside of the sector, that have developed similar management practices and whose knowledge should be mobilized to contribute to the improvement process. In both cases, IDB established specific partnerships with institutions willing to freely share and transfer their knowledge about the issues and needs identified.

Second, the establishment of a control tower[10] of two nurses, who had the responsibility to oversee compliance with optimal care time according to international standards. One nurse focuses on monitoring patients' pre-hospitalization care by managing available resources for medical consultation and by overseeing patient status to update doctors about their condition. The second nurse focuses on administrative procedures post-hospitalization by managing pending medical orders, identifying the reason for the delay delay for patients requiring extensive services, and updating medical information regarding all patients within the emergency service. Third, patients are classified according to their needs and the availability of resources. This step includes the consultation with the general practitioner.

It is important to clarify that, as a result of K4R, the changes in these three steps (admittance, control tower, and consultation) are adjustments to the clinic's operational schedule. They do not reflect any adjustment to the way physicians decide on medical treatment. The intervention only enables patients to go faster through the process.

10 This tracking scheme simulates an air traffic control tower and was adapted from knowledge exchange sessions with the AEROCIVIL. Two "control nurses" monitor the patient care process and and their cases, ensuring compliance with optimal management times under international standards, from admittance to discharge.

DATA

The sample includes data from the System Analysis Program Development (*SAP*), the information system of the INC of all patients visiting the clinic between August 1, 2018 and October 11, 2020. There were 15,788 visits during this 804-day period. Table 3 presents summary statistics of the daily data.

The intervention variable is Treatment, which is a dummy that takes the value 1 beginning March 10, 2020, the day that the operational changes in the visit process were implemented.[11]

The outcome variable is Days at clinic, which aims to capture the efficiency of the clinic's management. Days at clinic is the number of days that the patient spent in the clinic until being discharged. For patients who were discharged in less than a day, Days at clinic takes the value 1; for patients discharged between 1 and 2 days, Days at clinic takes the value 2, and so on. Finally, Patients is the total number of patients admitted to the clinic on the day of our observational unit.

11 The treatment period coincides with the expansion of COVID-19 cases. This is a concern regarding the external validity of our results since it would be difficult to extrapolate them to another environment unaffected by the pandemic. We believe that the fact that the clinic serves oncology patients in need of emergency services (unrelated to COVID-19) should mitigate this concern.

Table 3. Summary Statistics: Oncology Clinic

Variable	Observations	Mean	Standard deviation	Minimum	Maximum
Days at clinic	15,788	4.50	5.45	1	275
Treatment	15,788	.21	.41	0	1
Patients	15,788	43.33	14.04	1	79

Notes: The sample includes all patients (observational unit) entering the clinic on a given day from August 1, 2018 to October 11, 2020 (15,788 observations in 804 days). Days at clinic is the number of days that the the patient spent in the clinic until discharge. For patients who were discharged in less than a day, Days at clinic takes the value 1; for patients discharged between 1 and 2 days, Days at clinic takes the value 2, and so on. Treatment is a dummy that takes the value 1 for all patients since March 10, 2020. Patients is the total number of patients that entered the clinic on the same day of the observational unit.

ECONOMETRIC METHODS AND RESULTS

We want to assess the impact of K4R on the clinic's efficiency. Figure 3 summarizes our main result. The figure displays the evolution of a 28-day average corresponding to Days at clinic (waiting days from reception until discharge from the hospital). We consider bins of an average length of 28 days both before and after the intervention.

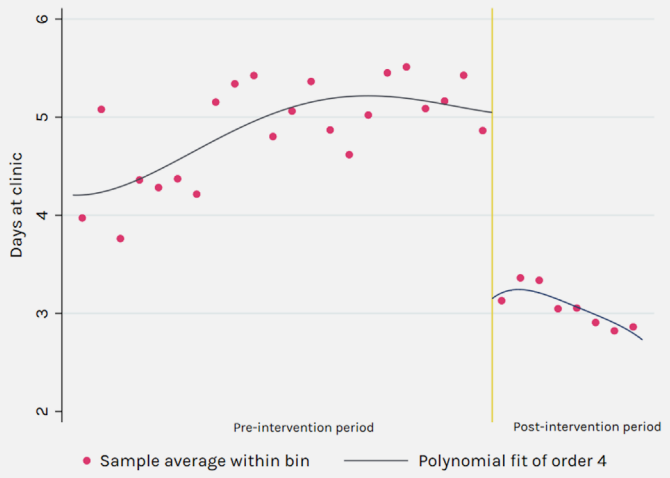


Figure 3 shows that the average number of days spent at clinic is significantly higher in the period before the intervention. Following the intervention, this number is sharply lower.

To formally address the impact of K4R on the clinic's efficiency, we use a regression discontinuity design to take advantage of the sharp discontinuity around the intervention date. Formally, we estimate the following regression:

$$Y_i = \beta\, Treatment_i + \delta\,(date_i - \tilde{x}) + \gamma Treatment_i * (date_i - \tilde{x}) + \Phi X_i + \varepsilon_i \qquad (3)$$

where Y_i is Days at clinic for patient i, is the $date_i$ in which patient i entered the clinic, $\tilde{x}$ is the cutoff date (March 10th, 2020), $Treatment_i$ takes the value 1 if patient i entered the clinic after the cutoff date and 0 otherwise, and ε_i is an error term. The set of controls includes the number of patients the clinic admitted during a given day and day of the week dummies (7 dummies, Monday to Sunday). The parameter of interest is β, the treatment effect at the cutoff.

Table 4 reports estimates of equation (3). The estimated coefficient for Treatment is in all cases negative and statistically significant, indicating that the intervention is associated with a reduction in the number of days patients stayed at the clinic.

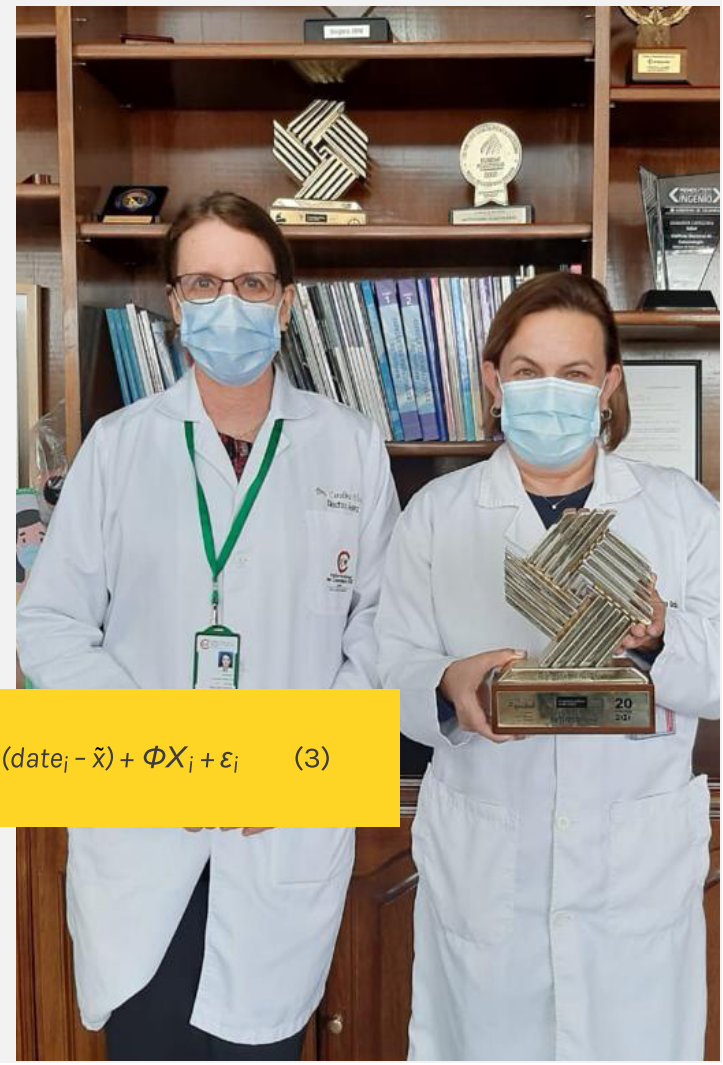


Table 4. Main Results: Oncology Clinic

	Dependent variable: days at clinic			
	(1)	(2)	(3)	(4)
Treatment	-1.265***	-1.288***	-1.125***	-1.130***
	(0.283)	(0.335)	(0.318)	(0.372)
	[0.000]	[0.002]	[0.001]	[0.009]
Day of week fixed effects	Yes	Yes	Yes	Yes
Patients	Yes	Yes	Yes	Yes
Observations	3,077	3,117	2,040	2,345

Notes: Columns (1) and (2) use a symmetric window of 82 and 84 days respectively to each side of the cutoff based on MSE-optimal bandwidth choice for robust bias-corrected inference (Calonico, Cattaneo, and Titiunik, 2014; Imbens and Kalyanaraman, 2012). In columns (3) and (4), we consider a narrower window of 51 and 60 days, respectively, to each side of the cutoff based on coverage error optimal bandwidth selectors (Calonico, Cattaneo, and Farrel, 2020). Columns (1) and (3) show heteroskedasticity-robust standard errors in parenthesis. Columns (2) and (4) show standard errors clustered by date in parentheses. In all specifications, the point estimator is computed using a linear local polynominal, while the bias correction is computed using a local quadratic polynomial. We report p-values of robust bias-corrected confidence intervals as reported in rdrobust (Calonico et al., 2017) in brackets. ***Significant at the 1% level.

The estimated coefficient in column (1) indicates an average reduction of about 1.2 days. Given that the sample mean of pre-intervention duration levels is 4.8 days, results imply an average reduction of 25 percent. RD estimates only consider visits within a certain window around the cutoff date (82 days, using the mean square error optimal bandwidth). In columns (3) and (4) of Table 4, we show that results are robust to considering a narrower window of time around the cutoff (between 51 and 60 days, using the coverage error optimal bandwidth).

Table 5. Alternative Specification: Oncology Clinic

	Dependent variable: ln(Days at clinic)			
	(1)	(2)	(3)	(4)
Treatment	-0.155***	-0.157***	-0.156***	-0.139**
	(0.049)	(0.057)	(0.059)	(0.064)
	[0.010]	[0.030]	[0.016]	[0.057]
Day of week fixed effects	Yes	Yes	Yes	Yes
Patients	Yes	Yes	Yes	Yes
Observations	3,310	3,450	2,199	2,597

Notes: Columns (1) and (2) use a symmetric window of 82 days to each side of the cutoff based on MSE-optimal bandwidth choice for robust bias-corrected inference (Calonico, Cattaneo and Titiunik, 2014; Imbens and Kalyanaraman, 2012). Columns (3) and (4) use a window of 55 and 66 days, respectively, to each side of the cutoff based on coverage error optimal bandwidth selectors (Calonico, Cattaneo, and Farrel, 2020). Columns (1) and (3) show heteroskedasticity-robust standard errors in parenthesis. Columns (2) and (4) show standard errors clustered by date in parentheses. In all specifications, the point estimator is computed using a linear local polynominal, while the bias correction is computed using a local quadratic polynomial. We report p-values of robust bias-corrected confidence intervals as reported in rdrobust (Calonico et al, 2017) in brackets. **Significant at the 5% level. ***Significant at the 1% level.

As an alternative specification, Table 5 presents the results of the same models in Table 4 but using the natural log of days at clinic as the dependent variable. Results show a statistically significant decrease of 15 percent in number of days from pre-intervention levels.

Finally, Table 6 presents manipulation tests based on local-polynomial density estimators (Cattaneo, Jansson, and Ma, 2017). We conducted two tests. In *Panel A*, we used a symmetric bandwidth of 51 days, which is the lowest choice in our main specifications in Table 4. In *Panel B*, we used a bandwidth of 82 days, the highest choice in our main specifications in Table 4. In both cases, we cannot reject the null hypothesis of no systematic manipulation of the running value at conventional significance levels. However, we got closer to rejection at the 10 percent level as we expanded the bandwidth. In our case, this implies that the number of patients decreased after the cutoff date, which is likely to be related to the expansion of COVID-19 cases during that period. We believe that the fact that we control for the total number of patients visiting the clinic in a given day should mitigate identification concerns.[12]

12 All results in Table 4 and 5 hold and remain fairly stable if we do not include covariates in the RD specifications.

Table 6. Manipulation Tests

Panel A	Left of cutoff	Right of cutoff
Effective observations	1,208	860
Bandwidth	51	51
Method	T	P > |T|
Robust	-1.089	0.276

Panel B	Left of cutoff	Right of cutoff
Effective observations	1,760	1,317
Bandwidth	82	82
Method	T	P > |T|
Robust	-1.629	0.103

Notes: This table shows the results of the manipulation tests based on local-polynomial density estimators using the stata command rddensity (Cattaneo and Jansson, 2018). The running variable is Date and the cutoff is March 10, 2020.

Conclusions and Discussion

5

K4R

Conclusions and Discussion

We study the impact of the K4R program on the efficiency of public agencies in Colombia. We present two examples on how K4R works. The first example is the Ombudsman's Office, which deals with citizens' petitions for access to basic services. The second example is an oncology clinic, which provides health care and emergency services to cancer patients. In both cases, we find that K4R is associated with a sizeable and statistically significant improvement in operational efficiency.

A simple back-of-the-envelope calculation indicates that K4R is a very efficient intervention from a cost–benefit perspective. In the case of the Ombudsman's Office, the economic benefit comes from time savings. Assuming that the reduction in time spent resolving petitions is uniformly distributed across regional offices and people within each team, our estimates indicate that public servants saved around 40 percent of their time spent processing a petition. We estimate the benefit as the product of the reduction in days needed to resolve a petition (68), the number of petitions in our sample (70,959), the fraction of the time public servants spent solving petitions (0.015), and the median daily wage in Colombia ($8.7). The estimated total benefit is approximately $630,000. In the case of the oncology clinic, patients now spend fewer days in the hospital. We estimate the benefit as the product of the number of days saved (1.2) per visit, the average daily wage (US$8.70), and the number of visits in the sample (15,788). The estimated total benefit is approximately US$165,000. Thus, considering the two interventions together, the total cost was US$60,000 and the overall benefit was around US$795,000, giving a ratio of US$12.20 saved per dollar invested.

Finally, in both cases, the quality of the service was fully guaranteed and get even better.

Internally, the managers of the processes in both institutions recognize an additional value of the experience. In the first case (Ombudsman), a significant improvement was "coordination and collaborative work" based on the model created and better knowledge of the organization at the central and the subnational level. As Giovanni Rojas, former National Director of Citizen Complaints, stated:

"Even though we had some clear rules, we found that we didn't understand each other's work and realities on the ground, especially in the remote offices of the Ombusman, such as the Amazonas. K4R allowed us to identifiy the real needs of our colleagues on a daily basis and establish a proper management model that considers that reality to improve our efficiency and, most importantly, to respond to citizens' complaints accurately and in a timely manner to ensure that health services are delivered and their rights are protected".

In the second case (National Cancer Institute), the knowledge shared was greater than mere technical aspects; it also allowed the staff to share their personal experiences for improving service delivery daily. As Dr. Martha García, coordinator of the INC's Group for Immediate Care to Cancer Patients, said:

"During the most critical months of the project, I went through one of the hardest trials of my life. I was diagnosed with an acoustic neuroma, a brain tumor, and had surgery at the Institute. As I went to my appointments and my evaluations, I saw my team together with the IDB team, both committed. It was wonderful to see that things were going forward and to realize that I had true friends committed to making it a reality".

Externally, complaints continued to be resolved fairly, and clinical outcomes did not deteriorate. As one of the patients of the National Cancer Institute stated:

"I appreciate Tatiana's work—the new "navigator" nurse, a role created by K4R—who in addition to quickly addressing my emergencies, had a human and caring approach that helps me face this challenge with hope and happiness. That's why I am drawing her, to express my gratitude for providing such high-quality service even in the most difficult of times". (see image below).

Given that weak states are a pervasive problem in the developing world and that large state reforms are difficult in practice, our contribution is to show that small changes, at minimal cost, can be effective tools to improve the quality of the bureaucracy. Future research should delve into whether our findings can be extrapolated to other environments and/or countries with different administrative cultures and regimes.

References

6

K4R

References

Alonso, J., J. Clifton, and D. Díaz-Fuentes. 2015. The Impact of New Public Management on Efficiency: An Analysis of Madrid's Hospitals. *Health Policy* 119(3): 333–40.

Amayah, A. 2013. Determinants of Knowledge Sharing in a Public Sector Organization. *Journal of Knowledge Management 17(3): 454–71.*

Andrews, R. and T. Entwistle. 2015. Public–Private Relationships, Administrative Capacity and Public Service Efficiency. *Policy & Politics* 43(2): 273–90.

Andrews, R. and S. Van de Walle. 2013. New Public Management and Citizens' Perceptions of Local Service Efficiency, Responsiveness, Equity and Effectiveness. *Public Management Review* 15(5): 762–83.

Arisi, D. et.al. 2020. Knowledge for Results – K4R. Washington, DC: Inter-American Development Bank.

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

Bousa, R. and K. Venkitachalam. 2013. Aligning Strategies and Processes in Knowledge Management: A Framework. *Journal of Knowledge Management* 17(3): 331–46.

Callaway, B. and P. Sant'Anna (2021). Difference-in-Differences with Multiple Time Periods. *Journal of Econometrics* 225(2): 200–30.

Calonico, S., M. Cattaneo, and Max Farrell (2020). Optimal Bandwidth Choice for Robust Bias-Corrected Inference in Regression Discontinuity Designs. *The Econometrics Journal* 23(2): 192–210.

Calonico, S., M. Cattaneo, M. Farrell, and R. Titiunik. 2017. Rdrobust: Software for Regression-Discontinuity Designs. *The Stata Journal* 17(2): 372–404.

Calonico, S., M. Cattaneo, and R. Titiunik. 2014. Robust Nonparametric Confidence Intervals For Regression-Discontinuity Designs. *Econometrica* 82(6): 2295–326.

Cattaneo, M., M. Jansson, and X. Ma. 2018. Manipulation Testing Based on Density Discontinuity. *The Stata Journal* 18(1): 234–61.

-----. 2020. Simple Local Polynomial Density Estimators. *Journal of the American Statistical Association* 115(531): 1449–455.

Downs, A. 1964. *Inside Bureaucracy.* Santa Monica, CA: RAND Corporation.

Earl, M. 2001. Knowledge Management Strategies: Toward a Taxonomy. *Journal of Management Information Systems* 18(1): 215–33.

Evans, P. and J. Rauch. 1999. Bureaucracy and Growth: A Cross-National Analysis of the Effects of 'Weberian' State Structures on Economic Growth. *American Sociological Review* 64(5): 748–65.

Finan, F., B. Olken, and R. Pande. 2015. The Personnel Economics of the State. NBER Working Paper 21825. Cambridge, MA: National Bureau of Economic Research.

Goodman-Bacon, A. 2021. Difference-in-Differences with Does Management Matter? Evidence from India Variation in Treatment Timing. *Journal of Econometrics* 225(2): 254–77.

Gruening, G. 2001. Origin and Theoretical Basis of New Public Management. *International Public Management Journal* 4(1): 1–25.

Imbens, G. and K. Kalyanaraman. 2012. Optimal Bandwidth Choice for the Regression Discontinuity Estimator. *The Review of Economic Studies* 79(3): 933–59.

Kamhawi, E. 2012. Knowledge Management Fishbone: A Standard Framework of Organizational Enablers. *Journal of Knowledge Management* 16(5): 808–28.

Lee, H. and B. Choi. 2003. Management Enablers, Processes, and Organizational Performance: An Integrative View and Empirical Examination. *Journal of Management Information Systems* 20(1): 179–228.

Omotayo, F. 2015. Knowledge Management as an Important Tool in Organisational Management: A Review of Literature. *Library Philosophy and Practice.*

Pérez-López, G., D. Prior, and J. Zafra-Gómez. 2015. Rethinking New Public Management Delivery Forms and Efficiency: Long–Term Effects in Spanish Local Government. *Journal of Public Administration Research and Theory* 25(4): 1157–83.

Quigley, N., P. Tesluk, E. Locke, and K. Bartol. 2007. A Multilevel Investigation of the Motivational Mechanisms Underlying Knowledge Sharing and Performance. *Organization Science* 18(1): 71–88.

Roodman, D., J. MacKinnon, M. Nielsen, and M. Webb. 2019. Fast and Wild: Bootstrap Inference in Stata Using Boottest. *The Stata Journal* 19(1): 4–60.

Schermerhorn, J. 1977. Information Sharing as an Interorganizational Activity. *Academy of Management Journal* 20(1): 148–53.

Weber, M. 1904–1911. Economy and Society. Guenther R. and Wittich, C. (eds). New York, NY: Bedminster.

Appendix

7

K4R

Stages of K4R

PLANNING		DESIGN		IMPLEMENTATION AND EVALUATION	
STAGE 1 **Scope and set-up** strategic, managerial, and operational	**STAGE 2** **Assessment** game-based, practical	**STAGE 3** **Mobilization** public–private knowledge	**STAGE 4** **Design** zero-cost solutions	**STAGE 5** **Piloting and measurement** of an experimental exercise	**STAGE 6** **Implementation and closure** of the intervention
1–3 months			1–3 months		1–2 months
Kickoff and definition of the scope of the intervention	**Analysis** of problems and identification of gaps	**Learning** based on exchange of know-how and practical, personal, and organizational experiences	**Adaptation** of ideas to tackle public problems	**Application** of tests to verify its effectiveness	**Magnification** of results to seek adoption and sustainability in public institutions
What and how Defining the intervention's horizon and objectives.	**In-house experts** Civil servants know their institution inside out—what works and what does not.	**What others do and how they do it** Firms or public institutions face the same dilemmas and will surely have identified successful alternatives for resolving them.	**Use of knowledge** The lessons learned mean that concrete solutions can be identified to address institutional needs.	**Testing and measurement** Experimenting and verifying the effectiveness of the proposed solutions.	**If it works, carry on!** Positive results drive adoption of solutions.
In practice					
• Evaluation of the highest authority's interests and priorities. • Choosing the work team: the IDB and its counterpart. • Definition of the scope and focus of the process to be improved. • Conceptual and methodological transfer by the IDB and professional training tailored to the institutional context.	• Institutional assessment characterizing the selected process and identifying gaps that affect performance. • Definition of current capacities and identification of opportunities for improvement. • Identification of needs and public, private, and/or third sector sources of knowledge that could participate.	• Management of partnerships with the relevant public, private, and/or third sector actors. • Development of knowledge transfer and exchange and/or co-creation workshops with public, private, or third sector partners.	• Definition of a pilot project, applying solutions such as: (i) Techniques existing in the institution that could be applied to adjust the process (ii) Adaptation of previous experiences implemented by the partners participating in the process (iii) New ideas that could possibly be implemented	• An experimentation exercise is carried out over a period of time and operation of the designed solutions is analyzed. • Metrics are generated that can express the achieved results.	• After measuring the results, the institution is encouraged to implement officially the successful solutions to ensure their adoption and sustainability. • Documentation of the process showing the results of the pilot. This is analyzed in light of an optimal short-, medium- and long-term operating model that integrates the action plan identified in the assessment. • The IDB writes a managerial report that includes results and findings for institutional decision making.