ARE PROJECTS BOOSTED TO GET APPROVED? EVIDENCE FROM TWO DECADES OF INVESTMENT APPRAISAL

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Alumno: César Ferreiro
Profesores Guía: Francisco Pino y Rodrigo Wagner

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Are projects boosted to get approved? Evidence from two decades of investment appraisal*

César Ferreiro P.
Universidad de Chile

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Abstract

A central goal of Finance is to allocate resources to the best projects, with rates of return that exceed the opportunity cost of funds. Importantly, though, empirical challenges have made that most of this financial research concentrates on the hurdle rates and cost of funds, leaving the black box of project preparation and appraisal as a relatively unexplored area. In this paper, we explore more than 28,000 public-funded investment projects between 1997 and 2021, which were prepared and evaluated in multiple rounds, receiving NPV and IRR. First, we find that the project's IRR distribution tends to have bunching just above the hurdle rate used as a cutoff for investment. This excess of mass was not an inherent property of the projects because when the pre-announced hurdle rate changed, the bunching also changed. We find evidence that projects closer to the hurdle rate tend to have longer iteration processes before receiving a passing IRR. Also, under some circumstances, they exhibit higher overrun costs and lower completion delays on the execution. We also find evidence that the technical capacities of project preparation units relate to fewer iterations before getting a passing IRR[1]. Overall, our evidence is coherent strategic models of project preparation and appraisal, either through "IRR management" (a parallel to earnings management, but for project appraisal) or a dynamic process of strategic "revise and resubmit" before the passing grade. The discussion suggests some implications for the design of project preparation processes.

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[1] Appendix H replicates the main results of the paper without considering projects presented between 2020 and 2021 due to potential differences generated by the pandemic crisis. Overall, results remain the same.

1 Introduction

Global capital spending in the non-financial corporate sector is well above a trillion dollars annually[2]. These investment decisions tend to be subject to some exercise of project appraisal. In a general setting, this involves accepting a project if the estimated rate of return (IRR) of the project is above some cutoff rate (hurdle rate) or rejecting it otherwise. While literature agrees that the hurdle rate does not necessarily coincides with the opportunity cost of the capital, there is a big empirical gap on how the presence of a hurdle rate affects the project preparation process, and therefore the estimated rate of return of projects. In this paper, we address the question if there is evidence of project preparation agents acting strategically to get their projects approved.

The presence of such a hurdle rate may induce a strategic behavior on project preparation agents. On the one hand, if the agent perceives a private benefit from the project being approved, this would generate incentives to distort information. On the other hand, if the costs of presenting a project are relatively low, this could lead to a process of sequential improvements before approval. Understanding how projects are prepared has important implications. In particular, it can be helpful to design mechanisms that both help avoid unwanted consequences, such as inefficiencies on capital allocation inside organizations, and induce some potentially desirable behaviors as truthfully revealing features of the project when there are asymmetries of information.

To understand how project preparation works, we present two families of models that include a strategic behavior by the agent who prepares the project. The first one incorporates a private benefit perceived by the agent if the project is approved. The main consequence is an upward bias on the reported values of the IRR (IRR management). The second describes project preparation as an iterating process where the agent sequentially acquires costly information about the project and decides whether to continue or quit the project (sequential improvements). We list empirical implications of these families of models and test them using information about 28,000 public-funded projects presented between 1997 an 2021 in Chile. These projects were prepared and evaluated by different state organizations, such as ministries, local governments, and state-owned firms, and presented to a central state unit that decided whether the projects were approved or rejected.

The main advantage of our setting is that we count with the stated rate of return of projects submitted for approval in periods where different hurdle rates were used. Thus, we can examine how stated rates of return react to changes in the hurdle rate. Also, we have information about the interactions between the unit in charge of the project's preparation and the unit deciding whether the project is approved or rejected, leading us to analyze the dynamics between these entities on the project preparation process. Finally, we count on information about two metrics of performance; overrun costs and project delay. This led us to give a better understanding of how project preparation is related to project quality.

Contrary to the literature which has focused on trying to understand what explains hurdle

[2]The Economist, Jan 27, 2016; citing a study from Citibank https://www.economist.com/buttonwoods-notebook/2016/01/27/what-happened-to-the-capex-boom

rates used by organizations (e.g.: Meier and Tarhan (2007), Jagannathan et al. (2016)), the main contribution of this paper is to offer empirical evidence on the study of project preparation based on project data. To our knowledge, this is the first paper analyzing both project's stated rate of return distribution and their reaction to changes in hurdle rates and showing evidence on the dynamics of project preparation, relating it to project performance.

Our main results show evidence of the project's reported rates of return reacting to the presence of hurdle rates. Moreover, we observe bunching of projects in regions just above hurdle rates. These results are consistent with models governed by a strategic behaviour by the agent who prepares the project. Also, and consistent with sequential improvements approach, we show evidence of heterogeneity in project preparation dynamics; weaker units take more time before project approval and abort more projects. Finally, we show evidence of bunched projects having differences in ex-post quality relative to non-bunched projects. These differences vary depending on the level of interaction between preparation units and the unit in charge of approval.

This paper is connected to at least three lines of the literature. First is financial economics literature on capital budgeting and the hurdle rates used as the cutoff for project approval. Second, is a tradition closer to accounting and finance, which speaks about miss reporting in variables. Third, our paper is related to the literature using bunching on empirical distribution as a way to measure behavior responses.

There is substantial empirical evidence showing that organizations use hurdle rates higher than standard calculations of the cost of capital could suggest (Poterba and Summers (1995)). This discrepancy is still an open question. A traditional point of view is that financially constrained firms ration their capital and forgo profitable investments opportunities. However, Jagannathan et al. (2016) concludes that non-financial constraints, such as limited qualified management or manpower, are the main reason why firms use hurdle rates above their cost of capital. Also, they find no evidence that high discount rates are used in the firm internal capital market to account for optimistic cash flow estimates. In brief, this literature indirectly makes claims of projects being accepted by looking at the cutoffs. However, they have not been able to look at the IRR distribution of projects applying to approval, and therefore study how projects are generated. This paper does.

Having agents in charge of project preparation acting strategically is similar to the so-called 'earnings management' documented in the corporate finance and accounting literature. Burgstahler and Dichev (1997) show evidence of firms managing earnings to avoid decreases and losses. Analogously, An et al. (2013) report that firms manipulate their financial statements in order to meet/exceed analyst forecasts. Other papers has emphasized the incentives of managers to distort financial information to improve their compensations (Bakke et al. (2016), Burns and Kedia (2006), Efendi et al. (2007)). Finally, Butt et al. (2016) find accounting manipulation in the quarters close to potential covenant violation. Our contribution is to show evidence of this phenomenon using project data. To our knowledge, this has not been done before.

Finally, the third link of this paper is related to the literature using bunching of empirical distributions to study behavior of individuals and firms. So far the main applications of this approach has been on the public finance literature (Saez (2010), Chetty et al. (2011), Kleven and Waseem (2013) Bastani and Selin (2014)). Our contribution is to bring some of this empirical machinery to the case of project preparation[3].

The rest of the paper is structured as follows. Section 2 describes a simple conceptual framework used to analyze the data. Section 3 describes the institutional information and the project data. Section 4 shows real correlates of bunching projects. Section 5 shows evidence of the dynamics of project preparation. Section 6 and 7 discusses the results and concludes.

[3]The use of empirical distributions to test strategic behavior has a wide range of applications. For example, Elliott et al. (2021) uses empirical distributions of p-values from published articles to test for p-hacking and publication bias.

2 Conceptual Framework

2.1 Traditional approach

There is a large tradition of papers in corporate finance literature aiming to explain why some projects are financed while others do not (Holmstrom and Tirole (1997), Fudenberg and Tirole (1990), Innes (1990), Diamond (1984)). Typically, an entrepreneur (the agent) asks for financing for a project from an investor (the principal). The main channels for credit rationing in this setting are moral hazard and adverse selection. However, due to the lack of data available, this literature does not delve into the project generating process. A typical assumption to overcome this issue is considering that project output comes from a known smooth probability distribution[4]. Although the distribution may depend on the agent's effort, this occurs after the financing has been obtained and therefore is more related to the execution than to the project's preparation[5]. Our focus through this paper is on the project preparation process.

2.2 Strategic approach

There are at least two families of models that include a strategic approach in the project preparation process. On the one hand, we can rationalize the incentives to estimate higher rates of return that the agent faces to get a project approved (IRR management). On the other hand, we can think of project preparation as a process of sequential improvements before the project is approved; the agent repetitively presents a project that can be accepted or rejected. If the project is rejected, the agent decides whether to reformulate the project and present it again or quit it. Figure 1 depicts the relation between the different families of model described.

The rest of the section delves into these two families of models mentioned.

2.2.1 IRR management hypothesis

Several theoretical papers have emphasized the scope for manipulation that arises in the presence of information asymmetry between the principal and the agent. For example, Matsusaka and Marino (2005) model points that when the principal retains the right to reject a project generates an incentive in the agent to communicate distorted information. Consistent with Wolk and Tearney (1997), who argue that while shareholders are only interested in maximizing return, managers have a wider range of preferences, Baldenius (2003) develops a model where managers enjoy non-pecuniary benefits of control ("empire benefits"). Wulf

[4]For example, Gale and Hellwig (1985) assumes that the return on an investment depends on the amount invested and a random state of nature.Analogously, Hart and Moore (1998) assumes that the returns of the project presented by the entrepreneur are realizations of a random variable. Moreover, they explicitly state that their model ignores any actions taken by the entrepreneur to generate returns.

[5]In Aghion and Bolton (1992) project returns depend on an action taken by the entrepreneur. However, this action is decided after the state of nature that determines the project's returns is realized.

(2009) highlights the inefficiency in resource allocation inside an organization due to the influence of division managers who distort capital budgets in their favor.

A model of IRR management in project preparation

In Appendix A.1 we present a principal-agent model for project preparation that includes the possibility of miss reporting. The principal pre-announces an approval rule for project approbation. The agent, who has private information about the real rate of return of the project, has to report a rate of return to the principal. The principal observes the reported value and decides whether the project is approved or rejected. In this model, if the agent perceives a private benefit for the project being approved, a rule such that the project is approved if the reported rate of return is bigger than a known hurdle rate cutoff (Naive CFO model) will induce misreporting from the agent. As a result, there is a range of values for the real rate of return where reporting higher values is a dominant strategy for the agent.

The rate of return can be viewed as a function that depends on prices and net benefits. Since prices are often observable by the two parts, a strategic agent would manipulate net befits to get a higher rate of return.

The testable implications for the Naive CFO model are:

IM 1. *There is bunching of projects just above the hurdle rate.*

IM 2. *A change in the hurdle rate granger-cause bunching above the new cutoff.*

IM 3. *If there is no perfect recall of a hurdle rate change, there would be bunching on the older cutoff due to agents targeting this value.*

IM 4. *If there is a probability of being caught on miss reporting, bunched projects are less likely to be monitored.*

Definition 1. *Let q_{ap} and q_{com} be vectors of project inputs estimated at the appraisal (ex-ante) and measured at completion (ex-post). We say a project is of low-quality type if and only if $IRR(q_{ap}) > IRR(q_{com})$. Analogously, if $IRR(q_{ap}) \leq IRR(q_{com})$ we say the project is of high-quality type.*

IM 5. *Bunched projects are of low-quality type.*

2.2.2 Sequential improvements hypothesis

Having agents sequentially deciding whether to modify or quit a project is similar to what happens on optimal stopping models. These models are characterized by the arrival of information over time and an agent deciding whether to stop or continue. This has been used to explain several phenomena in economics. Stigler (1962) and McCall (1970) uses it to model job search. McDonald and Siegel (1986) models the optimal timing for an irreversible investment. In finance, the pricing of an American option is modeled as an optimal stopping problem (McKean (1965)).

A model of sequential improvements for project preparation

In appendix A.2 we model project preparation as a sequential game with an optimal stopping rule. The game starts with the nature generating a perceived rate of return (IRR_0) for the project. The agent observes IRR_0. If it is greater than or equal to the hurdle rate cutoff (HRR), the project is accepted and the game ends. On the contrary, if IRR_0 is smaller than HRR, the agent decides between making a costly re-evaluation and re-submit the project or quit the project. The re-evaluation generates IRR_1, that with probability p is an improvement, such that $IRR_1 > IRR_0$, and with probability $1 - p$ has no effect and $IRR_1 = IRR_0$. The games continue until the project is accepted or the agent decides to quit it.

The testable implications of the sequential improvments (SI) model are: In the Optimal Stopping model there is bunching of projects just above the hurdle rate.

SI 1. *If the hurdle rate changes there would be bunching above this new cutoff.*

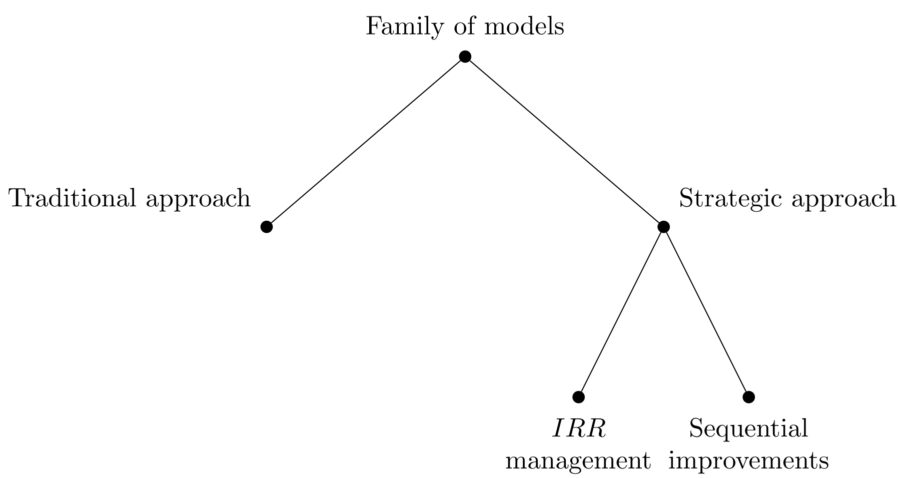
SI 2. *Projects with an IRR closer to the hurdle rate makes more iterations.*

SI 3. *Bunched projects are of high-quality type.*

Definition 2. *If two agents i and j differ in their probabilities of making an improvement p_i and p_j, we say that i is weaker than j if and only if $p_i < p_j$.*

SI 4. *Approved projects by weaker units (i.e with a lower probability of making an improvement) make more iterations before approval.*

SI 5. *Weaker units quit more projects.*



Notes: This figure depicts the relation between the different families of models described.

Figure 1: Families of models

Table 1 summarizes the testable implications under the different families of models described. Every row is particular empirical output, and the columns contain the predictions for that output under the models described. Rows (i)-(iii) have implications related to the distribution of the project's rate of return and their relation with the hurdle rate used by the principal. The main difference between IRR management and sequential improvements hypothesis is that, under the first, we expect to observe bunching of projects above the previous period's hurdle rate. On the contrary, we only expect bunching of projects above the current period hurdle rate under the former. This discrepancy reflects that under IRR management hypothesis, agents target specific values while under optimal stopping don't. Row (iv) contains the prediction of bunching projects characteristics under the manipulation hypothesis. In this case, we should expect that bunching projects are less likely to be monitored by the principal. Row (v) shows the different predictions for the ex-post quality of bunching projects. In particular, under the IRR management hypothesis, we expect bunching projects having a higher concentration of ex-post low-quality projects than non-bunching projects due to potential miss reporting at the appraisal. On the contrary, under sequential improvements, we should not observe more concentration of low-quality projects on bunched projects. Finally, Rows (vi)-(viii) contains the implications related to the project preparation process.

Empirical implications	**Traditional Approach**	IRR **Management**	**Sequential Improvements**
(i) Bunching of projects above period's HRR	No	Yes	Yes
(ii) Change in the HRR generates bunching above the new cutoff	No	Yes	Yes
(iii) Bunching of projects above previous cutoffs	No	Yes	No
(iv) Bunching projects characteristics	-	Projects with a lower probability of being monitored	-
(v) Project quality type	-	Low-quality type	High-quality type
(vi) Iterations before getting a project approved	-	-	More on weaker units
(vii) Aborted projects	-	-	More on weaker units
(viii) Projects closer to the HRR	-	-	Projects with more iterations

Notes: This tables summarizes the testable implications for the models delivered under both IRR management and sequential improvements hypothesis. Boxes with a horizontal line means there is no explicit prediction for the model in the row. HRR refers to the hurdle rate used to get the project approved. Weaker units refers to agents with a lower probability of making an improvement on project preparation according to the model presented on A.2.

Table 1: Summary of testable implications

3 Data

As we point in the previous sections, a typical limitation in this research line is the lack of information about evaluated projects inside an organization to conduct statistical analyses. One key advantage of our setting is that we observe information about approximately 28,000 projects inside an organization. For a portion of projects, we have their stated rate of return in periods with different hurdle rates cutoffs for approval. Thus, we can observe the empirical distribution of the stated rate of return and its reaction to variations in the hurdle rate cutoff. Also, we count on project preparation information; this describes the process followed by the preparation units before getting a project approved or rejected, this led us to test implications related to the dynamics of project preparation.

3.1 Institutional information

Project data comes from the National Public Investment System of Chile (SNI), which currently depends on the Ministry of Social Development and Family of Chile (MDSF). The Chilean SNI is the first and more robust public investment system in Latin America (Gómez-Lobo (2012)). Its origins date back to the 1950s, but it is since the 1980s that all public investment projects must apply to the SNI to determine whether it is funded or not (Fontaine (1997)).

The SNI is in charge of reviewing all projects applying to public funding and decide whether the project is approved or not. A project is composed by a series of stages that are approved and financed sequentially. Table 2 describes the different stages of a project. It is not mandatory that a project passes through every stage or that it starts in the first one. The requirements vary depending on the sector and the size of the project [6] [7].

The approval of every stage is an iterative process between the parties involved. Figure 2 depicts the process of aprobation of a project stage. The process starts when the prepration unit (PU) presents the initiave to the financial unit (FU), whose responsability is to submit it to the national investment system (SNI). Then, The MDSF verifies if it is admisible [8] and responds to the FU. If the initiative is declared non-admissible the PU can make the modifications requiered by the MDSF and ask to the FU to re ingress it in the SNI. The first time a stage is declared admissible, the project officially enters the SNI and is reviewed in detail. The MDSF reviews the evaluation made by the PU and chooses an answer between three options (RATE): successfully recommended' (RS), 'missing information (FI),

[6] Requirements by sector: http://sni.ministeriodesarrollosocial.gob.cl/evaluacion-iniciativas-de-inversion/evaluacion-ex-ante/requisitos-por-sector-para-formulacion-de-proyectos-nuevos-sectores/.

[7] Requirements for first stage: http://sni.ministeriodesarrollosocial.gob.cl/evaluacion-iniciativas-de-inversion/evaluacion-ex-ante/normas-instrucciones-y-procedimientos-inversion-publica-nip/

[8] An initiative is declared admissible when it contains all the documents required for the stage that is applying to. This information is available on http://sni.ministeriodesarrollosocial.gob.cl/evaluacion-iniciativas-de-inversion/evaluacion-ex-ante/normas-instrucciones-y-procedimientos-inversion-publica-nip/

or 'technically objected' (OT). If the RATE is favorable (RS), the FU can request the funds for the project. One of the requirements to obtain a RS is that the project's rate of return (when is evaluated with cost-benefit analysis) has to be greater or equal to a fixed hurdle rate cutoff defined ex-ante by the Ministry. On the contrary, if the stage application is not correctly formulated, it receives an FI or OT by answer. In this case, the PU can fix the initiative according to The MDSF comments. If so, the PU sends the initiative with corrections to the FU, whose responsible for sending it to The MSDF.

The institutional setting has similarities with both, IRR management and sequential improvements hypothesis. First, as in sequential improvements, the approval process considers the option of modifying the project before its approval. This happens when the MDSF rejects the stage approval, and the preparation unit can fix the application or quit the project. And second, similar to IRR management, there is an approbation rule known ex-ante by the agent that presents the project. In particular, if the project is evaluated using cost-benefit analysis, the reported rate of return has to be greater or equal to the pre-announced hurdle rate.

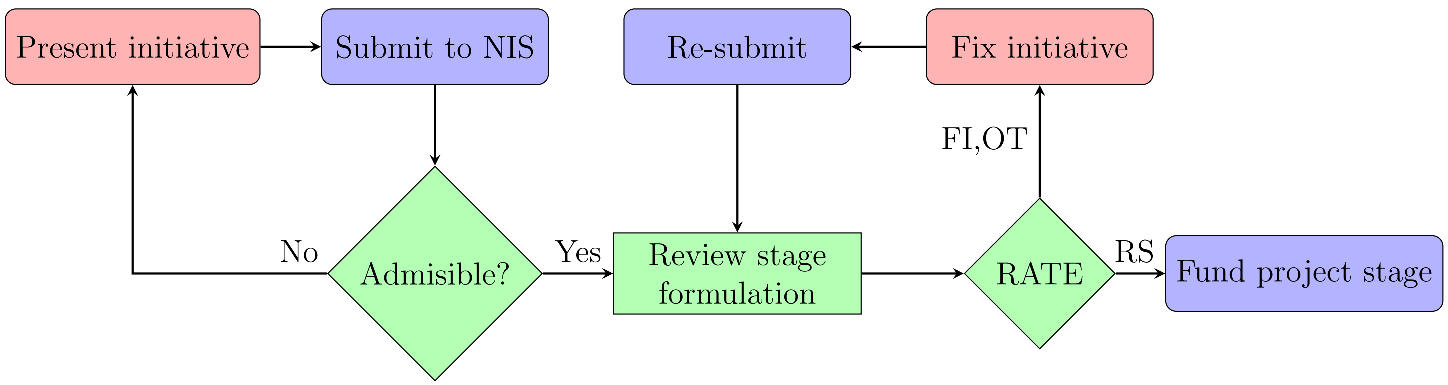
Potential channels for manipulation

We can think of the rate of return of a project as a function that depends positively on the product between discounted net benefits and prices. Thus, if we assume that cash flows are correctly assigned in the years of the project, there are two options to manipulate the rate of return; overestimating net benefits or prices. In both cases the result is a higher rate of return. However, in our setting prices are fixed by the Government, leading no option to manipulate this variable. For example, if the PU evaluates a new road's construction, one of the benefits could be the time saved by people who would use the new road; this could be expressed as time saved with the new road times the number of people benefited times the social price of time. Since the social price of time is fixed, the variables exposed to manipulation are the number of beneficiaries and time saved with the new road. Another option with the same result is to underestimate the cost of building the new road, thus net benefits are higher.

Stage	Description
Pre-feasibility	Preliminary evaluation of different solution options to the identified problem. In this stage, non-feasible options are discarded, and the best technical-economic alternative is selected.
Feasibility	The best-selected alternative is deepened and perfected.
Design	Development of plans (architecture and engineering), a detailed budget for civil works, equipment, and staff requirements.
Execution	Completion of works and acquisition of equipment for its development.

Notes: This table shows the stages of the project life cycle. It is based on the information of the SNI available on http://sni.ministeriodesarrollosocial.gob.cl/download/normas-instrucciones-y-procedimientos-inversion-publica-2020/?wpdmdl=3913.

Table 2: Project life cycle



Notes: This figure depicts the approval process of each stage of a project. Red figures represent activities developed by the preparation unit (PU), green figures those in charge of the ministry (MDSF), and blue ones those in charge of the financing unit (FU). RATE is the result of the technical-economical evaluation. Its possible outputs are lack of information (FI), technically objected (OT), and satisfactory recommended (RS).

Figure 2: Stage approval process

3.2 Sources of data

We count on three types of administrative data of projects. The first one is the economic evaluation sample, which consists of 7.7 K projects evaluated using cost-benefit analysis. Each project has the internal rate of return (IRR) and, in some cases, the social-NPV. Both are estimated at the appraisal by the preparation unit in charge of the project. Then we have the project preparation sample, with information about 28.5 K projects at the year-stage level of the RATE obtained and the number of iterations. This sample also contains variables describing the scope of the project, the preparation unit and the type of organization[9]. Finally, the ex-post evaluation sample is a set of 570 projects with information about the cost and the execution time of the project estimated at the appraisal and measured once the project was finished. Importantly, the MDSF does not declare any pre-established criteria for choosing projects for the ex-post evaluation. Appendix B shows the detail of all variables and the overlap between the three data samples described. Additionally , we count with the following common attributes to all the projects: project sector[10], preparation unit, the stage and the year of the project when entered the SNI (Stage and Year) and the financial source of the project.

3.2.1 Constructed variables

For the projects on the economic evaluation sample, we create the variable HRR that corresponds to the hurdle rate used the year the project entered to the SNI. Formally

$$HRR = \begin{cases} 12 & \text{if Year} \in [1997, 2000] \\ 10 & \text{if Year} \in [2001, 2004] \\ 8 & \text{if Year} \in [2005, 2008] \\ 6 & \text{if Year} \geq 2009 \end{cases}$$

Using HRR, we define two variables. The first one is the binary variable 'bunching', that takes the value one if the IRR is between HRR and $HRR + bw$, where bw is a predefined bandwidth[11]. The second one, HRR-distance, correspond to the distance between HRR and IRR for every project. Finally, we define the variable 'preparation unit type' that aggregates different preparation units into specific groups. Table 20 displays the different groups identified for the specific preparation units.

In the project preparation sample, we first define the variable 'Total iterations' as the sum of the iterations done by a project through all the years and stages. Second, we create the stage level variable 'Iterations before RS' that is the sum of iterations done by a project on a specific stage before getting a RS[12]. Third, we create the variable 'N-stages' as the number of stages that a project applied through its life cycle. Finally, we create the binary variable

[9]There are four type of organizations: Municipalities, Ministries, Firms (state owned firms) and Other.

[10]Transport, healthcare, education, segurity, etc.

[11]We refer to projects with the bunching variable equal to one as bunching projects.

[12]This variable is only created for the stages where the project obtained a RS.

'Attrition' that takes the value one when the last RATE of a project was not favorable and is from two or more years ago.

For projects on the ex-post evaluation sample, we create the variable 'Overrun costs' as log(cost ex-post)$-log$(cost ex-ante) and 'Completion delay' as log(observed execution time)$-$ log(estimated execution time)

3.3 Descriptive statistics

Table 3 describes the principal numerical variables from the three samples mentioned above. The first block describes variables from the economic evaluation sample. In the case of the IRR we only consider projects with a value lower than 600, this is equivalent to the 95% percentile of the sample. The discrepancy in the number of observations between IRR and log(social-NPV) is due to projects without social-NPV information. The second block correspond to the variables created with the project preparation sample. Total iterations, N-stages and Attrition are at project level, while Iterations before RS is a the project-stage level. Lastly, the third block displays variables from the ex-post evaluation sample with the variables creted overrun costs and delay.

Variable	N	mean	sd	p10	p50	p90
IRR	7,244	19.3	36.38	1	11	36.2
log(social-NPV)	5,727	10.44	5.53	0	11.64	16.36
Total iterations	28,521	5.49	5.09	1	4	12
N-stages	28,521	1.14	0.37	1	1	2
Iterations before RS	19,814	3.14	1.97	1	3	6
Attrition	28,521	0.25	0.43	0	0	1
log(estimated execution time)	571	13.2	1.3	11.8	13.1	15.2
log(observed exectuion time)	571	13.2	1.3	11.6	13.0	15.1
Overrun costs	571	-0.06	0.22	-0.26	-0.06	0.14
log(ex-ante duration)	571	2.23	0.58	1.61	2.20	3.04
log(ex-post duration)	571	2.62	0.76	1.61	2.56	3.66
Completion delay	571	0.38	0.62	-0.36	0.31	1.20

Notes: This table describes the principal numerical variables. The first block contains the variables from the economic evaluation sample. The second block displays variables created from the project preparation sample, and the third block are the variables from the ex-post evaluation sample.

Table 3: Summary statistics

Table 19 displays the concentration of projects without social-NPV among the different years. The two years with the higher concentration are 2010 and 2011. These years were characterized by the reconstruction made by the government after the 2010 earthquake[13]. Thus, is possible that projects without social-NPV are of different nature where the preparation unit, in this case the government, has some range of discretion on the projects that are executed.

[13] https://www.oecd.org/governance/toolkit-on-risk-governance/goodpractices/page/chilesreconstructionprocess.htm

4 Bunching on the ex-ante IRR distribution

In this section, we test if there is evidence of bunching on the ex-ante IRR distribution. This is related to both IRR management and sequential improvements hypothesis. If not rejected, it led us to move from the classic hypothesis of a smooth distribution on the rate of return of projects in favour of the strategic approach. First, we look at the graphical evidence. Then we apply the classic methodology used in the bunching literature and argue why it does not fit our setting. Finally, we propose a procedure that is more suitable for our setting. We find evidence of bunching in the IRR distribution under the three approaches used.

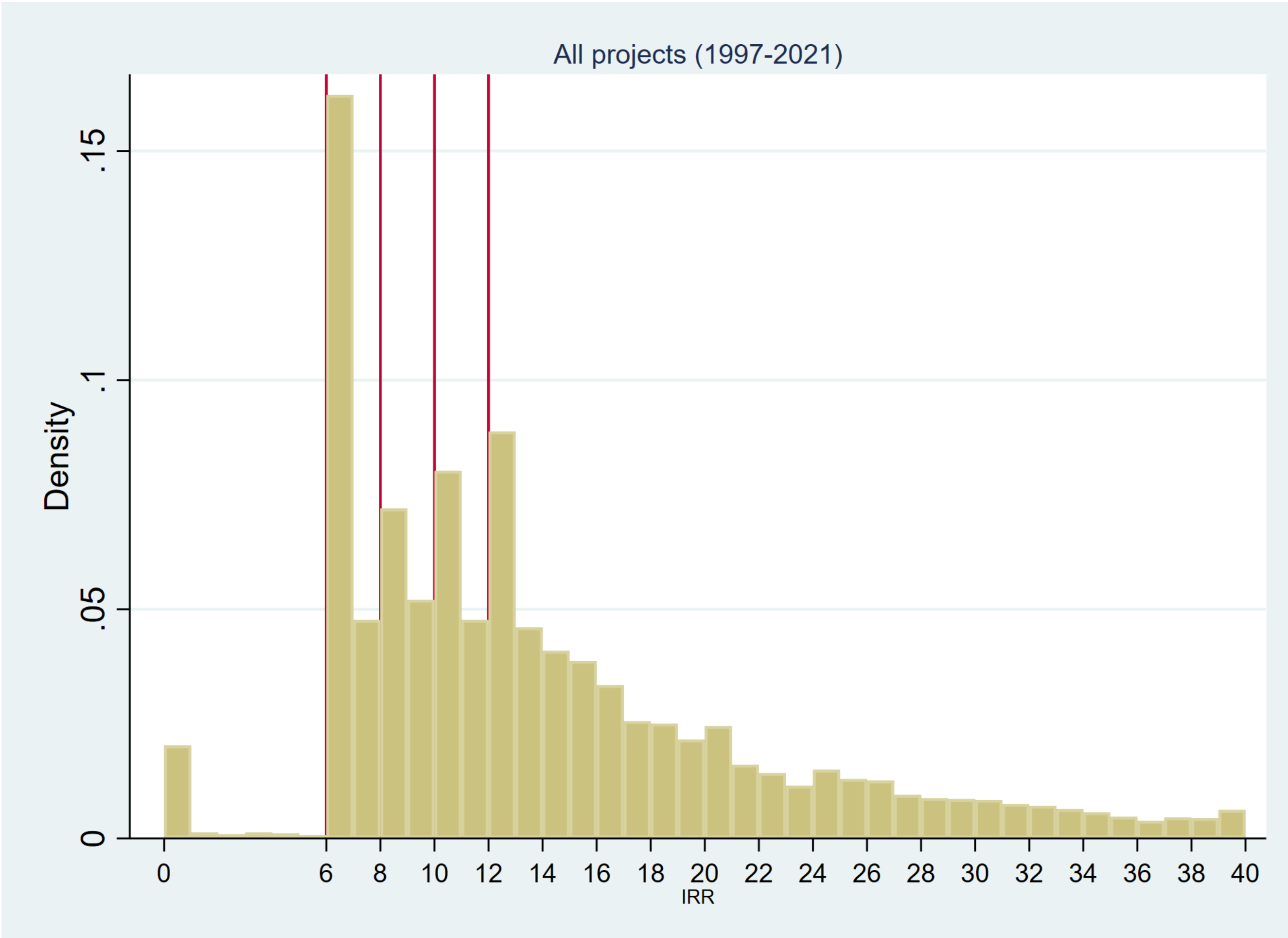
4.1 Graphical evidence on IRR bunching

We start looking at the distribution of the reported IRR of the projects made by preparation units at the appraisal. Figure 3 displays the IRR distribution for all the projects submitted between 1997 and 2021. Vertical red lines indicate hurdle rates used in this period. We notice two facts. First, there are almost no projects below the lowest and latest hurdle rate used (6%). The second one is that we observe bunching of projects in all the bins containing hurdle rates. These two facts suggest both agents are not presenting projects due to a rate of return below the hurdle rate and agents targeting specific values on the reported rate of return.

Figure 4 shows the distribution of the reported IRR in the periods defined by the different hurdle rates used, where each project is assigned to the period where entered to the SNI [14]. The red lines indicate the period's hurdle rate, and the blue ones the hurdle rates used in previous periods. First, we notice that in each period, there are almost no projects under the current hurdle rate, but as the hurdle rate decreases, we start observing projects with lower rates of return. For example, in 2005-2008 ($HRR = 8\%$), project density in $[6, 8)$ is approximately 0%, but in 2009-2021, when the hurdle rate moves to 6% , we observe around 50% of projects in this interval. Also, we can see an bunching of projects on bins over the previous period's hurdle rates. Moreover, in the period 2001-2004, bins containing the hurdle rate of the previous period (12%) is the one with the higher concentration of projects and in period 2005-2008 the bin containing the hurdle rate 10% is the second one with more concentration of projects. These observations suggest both agents reacting to changes in the hurdle rate and a lag in the perceptions of the current hurdle rate.

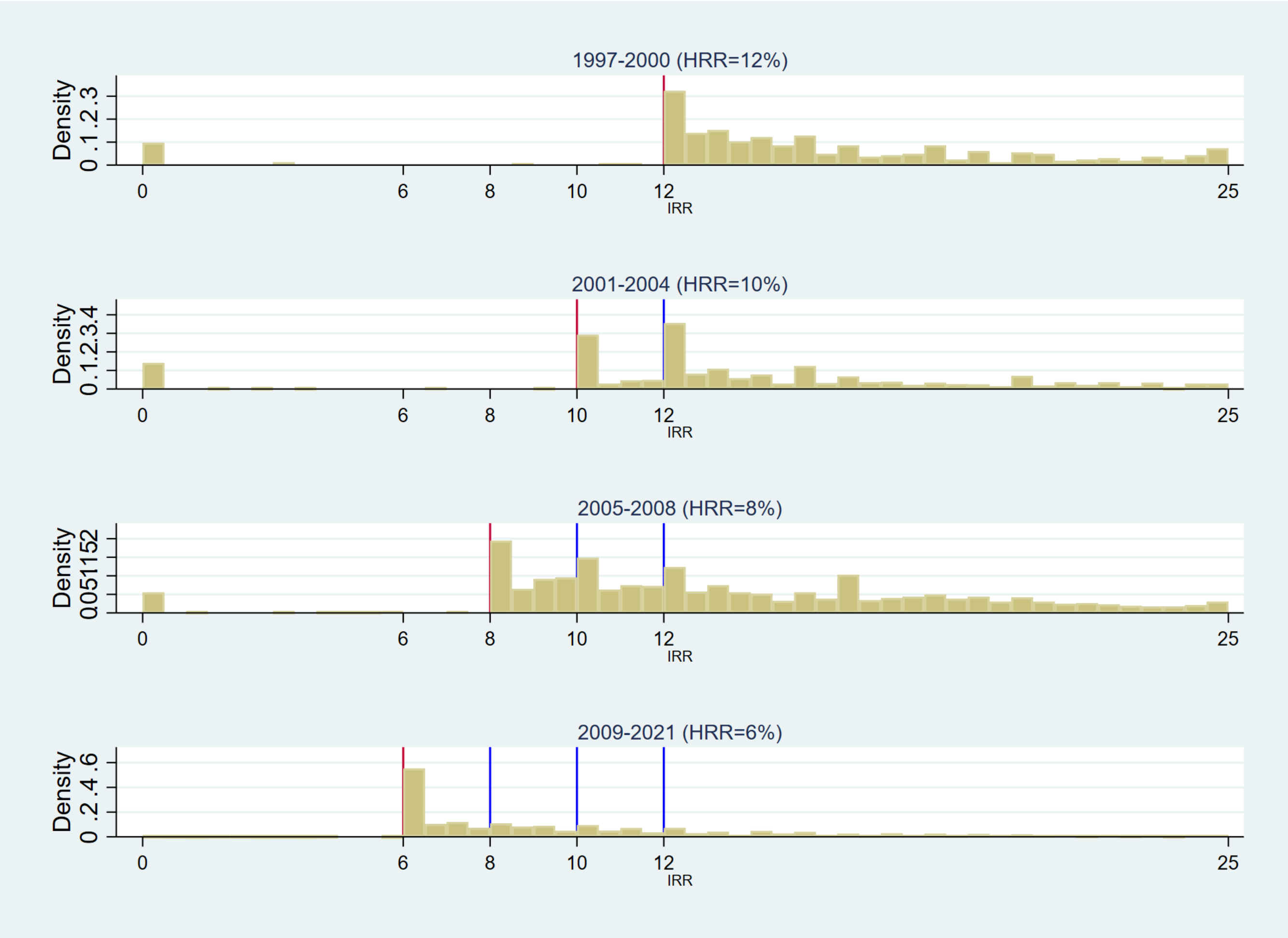
Appendix E displays the distribution of the ex-ante IRR distribution only considering projects that has social-NPV information. In the period 2009-2021 there is no an evident excess of projects over hurdle rates. However, on previous periods we still can see projects concentrated just above the hurdle rates used.

[14] Appendix D depicts another version of this figure which shows the shape of the IRR distribution.



Notes: This figure depicts the distribution of the ex-ante IRR made by preparation units between 1997 and 2021. Red lines correspond to the different hurdle rates used in this period. 2009-2021 (HRR=6%) , 2005-2008 (HRR=8%), 2001-2004 (HRR=6%) and 1997-2000 (HRR=12%).

Figure 3: ex-ante IRR distribution (1997-2021)



Notes: This figure depicts the distribution of the ex-ante IRR in the periods defined by the different hurdle rates used. Red lines correspond to the period's hurdle rate and blue lines a previous period's hurdle rates.

Figure 4: ex-ante IRR distribution by HRR-period

4.2 Classic Approach to test IRR bunching

Now we want to test statistically if there is bunching using the methodology proposed by Kleven and Waseem (2013) adapted to the case where the bunching zone is above the cutoff. We divide projects into 0.5 IRR bins (as in Figure 4) and for each period we estimate the following polynomial regression[15]:

$$\underbrace{\frac{N_{jt}}{N_t}}_{\substack{\text{Percentage of projects}\\ \text{in bin } j \text{ on period t}}} = \underbrace{\sum_{k=0}^{q} \beta_k (y_j)^k}_{\text{Polynomial term}} + \underbrace{\sum_{i=y_{lb}}^{y_{ub}} \gamma_i \cdot 1[y_j \in [i, i+0.5)]}_{\text{Intercept shifters}} \tag{1}$$

Where N_{jt} is the number of projects in bin j on period t [16], N_t is the total number projects on period t, y_j is the middle point of bin j, γ_i are the intercept shifters for the bins in the excluded interval $[y_{lb}, y_{ub} + 0.5)$ and q is the degree of the polynomial. With the estimated coefficients we define the counterfactual distribution as:

$$\widehat{\left(\frac{N_{jt}}{N_t}\right)} = \sum_{i=0}^{q} \widehat{\beta}_i \cdot (y_j)^i$$

We use the counterfactual distribution to estimate the missing mass to the left of the hurdle rate cutoff (H) and the excess of mass to the right of this cutoff (B):

$$\widehat{H} = \sum_{j \in [y_{lb}, HRR)} \left[\widehat{\left(\frac{N_{jt}}{N_t}\right)} - \left(\frac{N_{jt}}{N_t}\right) \right] \quad \text{and} \quad \widehat{B} = \sum_{j \in [HRR, y_{ub}+0.5)} \left[\left(\frac{N_{jt}}{N_t}\right) - \widehat{\left(\frac{N_{jt}}{N_t}\right)} \right]$$

To define the exclusion interval $[y_{lb}, y_{ub} + 0.5)$, we assume that the missing mass coincides with de bunching mass, thus $B = H$. We start defining y_{ub} as the lower bound of the bin that contains the hurdle rate cutoff of the period, then we set $y_{lb}^0 = HRR - \epsilon$ and estimate the ratio $\widehat{B^0}/\widehat{H^0}$. In the next iteration we update the lower bound value to $y_{lb}^1 = y_{lb}^0 - \epsilon$ and calculate the ratio again. We repeat this process until we get $\widehat{B^k} \approx \widehat{H^k}$. With the exclusion interval defined, the bunching estimator corresponds to the ratio between the excess of bunching mass above the cutoff and the average counterfactual distribution in the excluded interval below the cutoff:

$$\widehat{b} = \frac{\widehat{B}}{\frac{1}{n_{lb}} \sum_{j \in [y_{lb}, HRR)} \widehat{N}_j} \tag{2}$$

Where n_{lb} is the number of bins in the interval $[y_{lb}, HRR)$.

Table 4 display the results obtained when we calculate the bunching estimator over the current period's hurdle rate cutoff using $y_{ub} = HRR$ in each period[17]. We take as benchmark

[15] For this section we only consider projects with an IRR lower or equal than 80.

[16] bin j is defined by the inerval $[j, j + 0.5)$

[17] For examle in period 2009-2021 we use $y_{ub} = 6\%$.

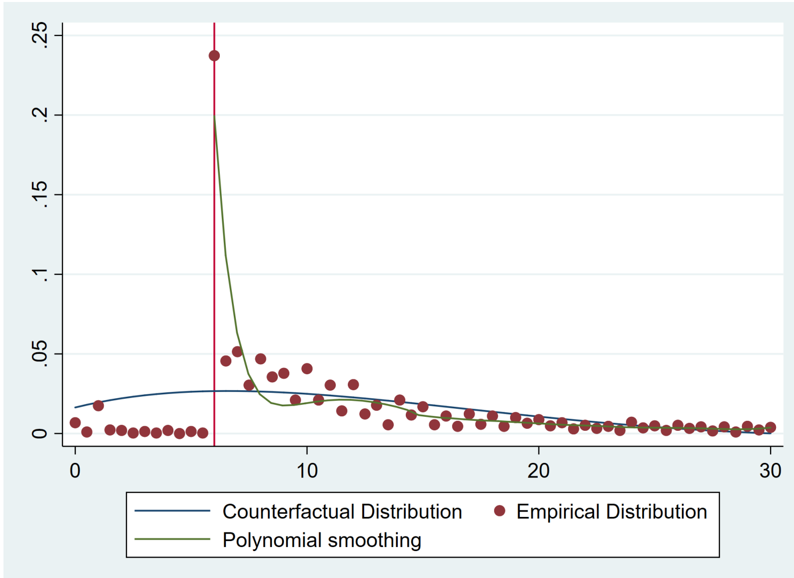
Almunia and Lopez-Rodriguez (2018) who selects the lower bound y_{lb} as the first point that makes the ratio $\widehat{B}/\widehat{H} \in [0.9, 1, 1]$.

Although we find significant bunching estimates for all periods, there is a problem on applying this methodology in our setting. One fundamental assumption of this methodology is that there is no extensive-margin response of the agents who are reporting. Otherwise, the counterfactual distribution estimated would not be a 'true counterfactual'. In our setting the assumption of no extensive-margin response means that the hurdle rate presence does not affect the decision of presenting a project but only the reported IRR. This seems unrealistic in out setting. As we argue in Section 4.1 the presence of the hurdle rate might be causing what projects are presented. Figure 5 depicts the observed distribution and the estimated counterfactual distribution for period 2009-2021. The counterfactual distribution is strictly increasing from 0 to a point located above the hurdle rate. This means that in the absence of a hurdle rate cutoff, there would be more projects with a high rate of return than a lower one. The principal consequence of using a counterfactual distribution as this one, is we are overestimating the bunching estimator.

Period	$\widehat{b}$	$\widehat{B}$	$\widehat{H}$	$\widehat{B}/\widehat{H}$	y_{lb}	$y_{ub} + 0.5$
1997-2000 (HRR=12%)	5.36 (0.75)	0.100	0.105	0.95	9.0	12.5
2001-2004 (HRR=10%)	4.67 (0.88)	0.092	0.09	1.02	7.5	10.5
2005-2008 (HRR=8%)	2.75 (0.42)	0.528	0.537	0.98	6.5	8.5
2009-2021 (HRR=6%)	8.65 (0.65)	0.21	0.20	1.01	1.5	6.5

Notes: This table reports the bunching estimates above the period's hurdle rate according to equation (2). $\widehat{b}$ is the average bunching estimator, boostsrapped standard errors are shown next to each estimate in parentheses. $\widehat{B}$ is the percentage of projects above the counterfactual distribution in the range $[HRR, y_{ub}+0.5)$, $\widehat{H}$ is the percentage of projects below is the missing mass of projects in the range $[y_{lb}, HRR)$.

Table 4: Bunching estimators



Notes: This figure shows the estimated counterfactual distribution (blue line), the observed concentration of projects in the 0.5% bins (red dots) and a polynomial smoothing for the empirical distribution above the cutoff (green line) for the period 2009-2021. The red line corresponds to the hurdle rate cutoff of this period (6%).

Figure 5: Estimated counterfactual distribution (2009-2021)

4.3 Proposed methodology to test IRR bunching

Since the absence of an extensive-margin response does not seem realistic in our setting, we can not use the methodology proposed by Kleven and Waseem (2013) to infer where the bunching mass comes from. However, we still can measure this excess of mass. To do this, we estimate the following basic polynomial model:

$$\underbrace{\frac{N_{jt}}{N_t}}_{\substack{\text{Percentage of projects}\\ \text{in bin } j \text{ on period t}}} = \underbrace{\sum_{k=0}^{q} \beta_k (y_j)^k}_{\text{Polynomial term}} + \underbrace{\sum_{i \in HRR_t} \gamma_i \cdot 1[i \in \text{bin} j]}_{\substack{\text{Intercept shifts for bins}\\ \text{containing hurdle rate cutoffs}}} \tag{3}$$

where HRR_t is the set of hurdle rate cutoffs used until period t[18]. With this specification $100 \cdot \gamma_i\%$ correspond to the percentage of excess of projects in the bin containing the hurdle rate i.

Table 21 displays OLS estimates for the polynomial model with $q = 5$. Columns (1)-(4) displays the results for the periods defined by the different hurdle rate cutoffs used. Columns (5)-(8) does the same but including a dummy variable that takes the value one if the bin contains an integer value. With this we control for the round number bias. In the four

[18]For example in the period 2005-2008 the hurdle rate cutoff was 8%, thus $HRR_{2005-2008} = \{8\%, 10\%, 12\%\}$.

periods we find excess of projects above the current and previous hurdle rate. For example in period 2009-2021 (column (8)), there is an excess of 21.9% (standard error 0.005) and 3% (standard error 0.004) on current and previous period hurdle rates.

A possible consideration of these results is we are implicitly using a counterfactual distribution with the same shape as the one used in the previous section. To overcome this, we repeat the estimations but using a polynomial with a structural brake around the hurdle rate:

$$N_{jt}/N_t = \begin{cases} \sum_{k=0}^{q} \delta_k (y_j)^k & \text{if} \quad max(\text{bin j}) < HRR \\ \sum_{k=0}^{q} \beta_k (y_j)^k + \sum_{i \in HRR_t} \gamma_i \cdot 1[i \in \text{bin} j] & \text{if} \quad min(\text{bin j}) \geq HRR \end{cases} \tag{4}$$

Table 22 shows OLS estimates for the polynomial with structural brake. First, we note that using a lower degree polynomial the model with structural brake provides a better fit than the basic model. For example for Period 2005-2008 (column (3)) we obtain an R^2 0.926 against 0.684 with the basic model (Table 21 column (8)). Second, the magnitude of γ_i coefficients tend to be smaller. For example, $\widehat{\gamma_6}$ moves from 0.219 (standard error 0.005) in the basic model to 0.201 (standard error 0.005) in the model with structural break or $\widehat{\gamma_8}$ in period 2005-2008 moves from 0.057 (standard error 0.003) to 0.04 (standard error 0.002). To sum, In all periods we still find significant excess of projects both above current and previous period's hurdle rate.

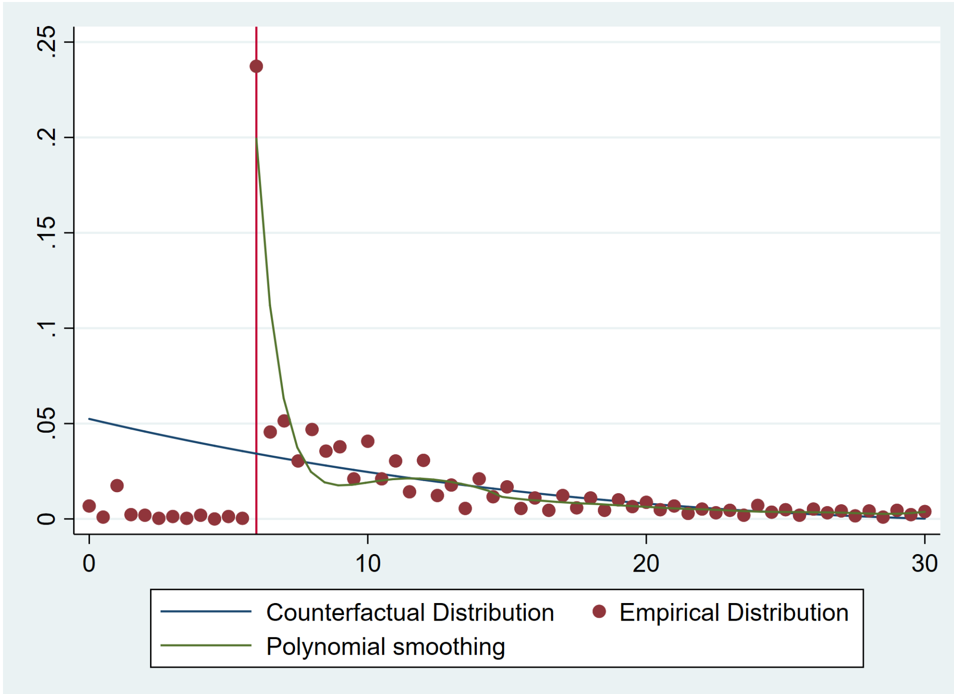
Using the $\widehat{\beta}$ coefficients estimated with the structural brake model, we can define a new counterfactual distribution as in the previous section. Figure 6 depicts the observed and counterfactual distribution using for Period 2009-2021. In this case, the estimated counterfactual distribution is strictly decreasing, which seems more realistic. Using this, we define the following bunching estimator over the hurdle rate cutoff i:

$$\widehat{b}_i = \frac{\widehat{\gamma}_i}{\sum_{k=0}^{q} \widehat{\beta}_k (y_{j(i)})^k} \tag{5}$$

where $j(i)$ is the bin containing the hurdle rate cutoff i and the denominator is the counterfactual distribution on the bin $j(i)$.

Table 5 shows the result of the proposed bunching estimator. Each column shows the estimator over the different hurdle rates. standard errors are in parenthesis and 95% confidence interval are in square brackets. We find significant estimator in all periods for current and previous hurdle rates used. Consistent with the fact that the classic approach underestimates the counterfactual distribution (i.e., bunching estimators are overestimated), when we compare the magnitude of bunching estimators over current periods hurdle rate (diagonal of the Table 5) with those estimated under the classing approach, we notice that now we obtain lower bunching estimates. For example, in 2009-2021, we move from a bunching estimator of 8.65 to 5.87.

Finally, this estimator led us indirectly test if the data we are observing corresponds to a truncated smooth distribution. If this were the case bunching estimators over the current period's hurdle rate should be zero. As Table 5, this is not the case and all bunching estimators over period's hurdle rate are statistically different from zero.



Notes: This figure shows the estimated counterfactual distribution (blue line), the observed concentration of projects in the 0.5% bins (red dots) and a polynomial smoothing for the empirical distribution above the cutoff (green line) for the period 2009-2020. The red line corresponds to the hurdle rate cutoff of the period (6%).

Figure 6: Estimated counterfactual distribution (2009-2021)

	Period			
	1997-2000 (HRR=12%)	2001-2004 (HRR=10%)	2005-2008 (HRR=8%)	2009-2021 (HRR=6%)
$\widehat{b}_6$	-	-	-	5.87 (0.27)
	-	-	-	[5.36 , 6.43]
$\widehat{b}_8$	-	-	1.31 (0.13)	0.53 (0.12)
	-	-	[1.08 , 1.55]	[0.29 , 0.81]
$\widehat{b}_{10}$	-	3.19 (0.38)	1.01 (0.12)	0.57 (0.12)
	-	[2.53 , 4.03]	[0.88 , 1.18]	[0.31 , 0.87]
$\widehat{b}_{12}$	2.09 (0.18)	4.97 (0.49)	0.91 (0.14)	0.39 (0.16)
	[1.72 , 2.50]	[4.11 , 6.05]	[0.72 , 1.09]	[0.02 , 0.7]

Notes: This table reports bunching estimators according to the equation 5. Bootstrapped errors are in parenthesis and 95% confidence intervals are in parenthesis.

Table 5: Bunching estimators using the proposed methodology

5 Real correlates of bunching projects

The past section showed that the IRR of submitted projects tend to bunch just above the hurdle rate. This section explores how bunching is related to the process of project appraisal and the outcomes of these projects. We first look at the number of iterations per stage on the "reject and resubmit" process of approved projects, with evidence of projects closer to the hurdle rate making more iterations per stage prior to a stage approval. Then we look at some proxies of execution quality, looking at overrun costs and completion delays. We find some evidence that bunched projects tend to have higher than expected costs and lower completion delays, although only some of the specifications are statistically significant. Finally, we split projects according to their number of iterations on the "reject and resubmit" process. We find evidence that bunched projects with high iterations have on average lower delays than non bunched projects, and bunched project with low iterations present higher overrun costs.

5.1 Bunching projects monitoring

According to IRR management hypothesis, bunching projects should be such that are less likely to be monitored. To test this empirical implication, we use average iterations per stage[19] of a project as a measure of how much the project is monitored. Thus, if IRR management hypothesis holds, we should expect that approved bunching projects exhibit a lower number of iterations per stage, and therefore are less monitored. The main assumption that we are doing is, if a manipulated project was approved, manipulation were not detected by the supervisory unit (MDSF).

Table 6 tests if approved bunching projects make less iterations per stage. We consider a project as being approved if the last stage that applied to got a RS. In all the specifications we use a 0.5 bandwidth for the bunching variable. Columns (1)-(5) controls by fixed effects at preparation unit-type level and (6)-(10) uses fixed effects at the specific preparation unit level. All specifications controls by sector, financial source and first stage fixed effects. Finally, we control by the logarithm of the number of stages, therefore bunching coefficient correspond to the ratio of average iterations per stage between bunching and non-bunching projects. In none of the estimations we find significant estimators for the coefficient associated to the bunching variable. Contrary to the implications of the IRR management hypothesis, this results suggest that approved bunching projects are not less monitored that the rest of approved projects. Moreover, the coefficients associated to the IRR variable are always negative although they are not significant in all specifications. This suggest that approved projects with a lower rate of return make more iterations per stage, which is related to sequential improvements hypothesis. To test this, we estimate the elasticity of average iterations per stage respect to HRR-distance. Table 7 displays OLS estimates of this elasticity. As in Table 6 Columns (1)-(5) controls by fixed effects at preparation unit-type level and (6)-(10) uses fixed effects at the specific preparation unit level. Also, all specifications

[19] log(Total iterations)-log(n-stages)

controls by sector, financial source and first stage fixed effects. We find that when we control by social-NPV as a measure of project's size the elasticity is negative and statistically significant in all specifications. Significant estimated values goes from -0.039 (p-val 0.002) to -0.013 (p-val 0.097).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES					*log*(total iterations)					
bunching	0.013	-0.016	0.058	0.033	0.022	0.025	-0.018	0.037	0.082	0.072
	(0.031)	(0.043)	(0.043)	(0.044)	(0.045)	(0.035)	(0.045)	(0.046)	(0.053)	(0.053)
log(social-NPV)			0.030***	0.028***	0.029***			0.023***	0.022***	0.025***
			(0.004)	(0.005)	(0.005)			(0.005)	(0.008)	(0.008)
IRR	-0.000	-0.000	-0.001*	-0.001	-0.002**	0.000	-0.000	-0.000	-0.000	-0.003**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
IRR^2					0.000**					0.000**
					(0.000)					(0.000)
log(n-stages)	1.184***	1.145***	1.130***	1.124***	1.123***	1.163***	1.128***	1.127***	1.117***	1.117***
	(0.041)	(0.044)	(0.044)	(0.047)	(0.047)	(0.044)	(0.048)	(0.047)	(0.063)	(0.063)
Constant	1.629***	1.642***	1.259***	1.279***	1.287***	1.623***	1.631***	1.325***	1.310***	1.308***
	(0.016)	(0.018)	(0.061)	(0.064)	(0.064)	(0.015)	(0.018)	(0.072)	(0.101)	(0.102)
Observations	2,556	2,093	2,093	2,036	2,036	2,408	1,949	1,949	1,453	1,453
R-squared	0.384	0.404	0.419	0.491	0.492	0.482	0.504	0.511	0.646	0.649
Projects	All	NPV	NPV	NPV	NPV	All	NPV	NPV	NPV	NPV
Preparation unit type FE	Yes	Yes	Yes	No	No	No	No	No	No	No
Year FE	Yes	Yes	Yes	No	No	Yes	Yes	Yes	Yes	Yes
Year x Prep Unit type FE	No	No	No	Yes	Yes	No	No	No	No	No
Preparation Unit FE	No	No	No	No	No	Yes	Yes	Yes	No	No
Prep Unit x Year	No	No	No	No	No	No	No	No	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: This table shows OLS estimates for the difference on average iterations per stage between bunching and non-bunching projects. Estimations are made using projects evaluated with cost-benefit analysis (i.e. with information of IRR and/or social-NPV) that got approved the last stage they applied to. The row projects indicates the sample of projects used, 'All' refers to projects with IRR and not necessarily social-NPV and 'NPV' projects with IRR and social-NPV information. In all the estimations we control by project sector, financial source and first stage fixed effects.

Table 6: Regressions explaining iterations in approved project

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
					log(total iterations)					
log(HRR-distance)	-0.010	-0.013*	-0.036***	-0.027***	-0.022*	-0.006	-0.010	-0.030***	-0.039***	-0.047***
	(0.007)	(0.008)	(0.009)	(0.009)	(0.013)	(0.008)	(0.009)	(0.009)	(0.012)	(0.016)
log(social-NPV)			0.034***	0.031***	0.031***			0.028***	0.028***	0.028***
			(0.005)	(0.005)	(0.005)			(0.006)	(0.008)	(0.008)
log(HRR-distance)^2					-0.002					0.003
					(0.003)					(0.004)
log(n-stages)	1.178***	1.136***	1.115***	1.113***	1.113***	1.149***	1.119***	1.117***	1.101***	1.103***
	(0.042)	(0.044)	(0.043)	(0.047)	(0.047)	(0.045)	(0.047)	(0.047)	(0.062)	(0.062)
Constant	1.644***	1.657***	1.256***	1.281***	1.283***	1.637***	1.649***	1.308***	1.301***	1.295***
	(0.018)	(0.020)	(0.060)	(0.063)	(0.063)	(0.019)	(0.021)	(0.072)	(0.103)	(0.104)
Observations	2,393	2,072	2,072	2,017	2,017	2,246	1,928	1,928	1,440	1,440
Projects	All	NPV	NPV	NPV	NPV	All	NPV	NPV	NPV	NPV
R-squared	0.391	0.406	0.424	0.494	0.495	0.492	0.507	0.515	0.647	0.647
Preparation unit type FE	Yes	Yes	Yes	No	No	No	No	No	No	No
Year FE	Yes	Yes	Yes	No	No	Yes	Yes	Yes	Yes	Yes
Year x Prep Unit type FE	No	No	No	Yes	Yes	No	No	No	No	No
Preparation Unit FE	No	No	No	No	No	Yes	Yes	Yes	No	No
Prep Unit x Year	No	No	No	No	No	No	No	No	Yes	Yes
elasticity	-0.010	-0.013	-0.036	-0.027	-0.025	-0.006	-0.010	-0.030	-0.039	-0.041
p-val	0.156	0.097	0.000	0.002	0.005	0.447	0.226	0.001	0.002	0.000

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: This table shows OLS estimates for the elasticity of iterations per stage respect to HRR-distance. Estimations are made using projects evaluated with cost-benefit analysis (i.e. with information of IRR and/or social-NPV) that got approved the last stage they applied to. The row projects indicates the sample of projects used, 'All' refers to projects with IRR and not necessarily social-NPV and 'NPV' projects with IRR and social-NPV information. In all the estimations we control by project sector, financial source and first stage fixed effects.

Table 7: Elasticity of average iterations per stage relative to HRR-dsitance in approved projects

5.2 Proxies of project quality around the hurdle rate[20]

Ideally, we would like to have a reliable measure of the ex-post rate of return of the projects and compare it with the declared rate of return at the appraisal. Thus, we could test if bunched projects exhibit a lower 'real' rate of return (i.e a lower quality) than non-bunching projects. We do not count on this information, but we can take advantage of the variables available in the ex-post evaluation; these compares the observed cost and execution time of a project with the cost and execution time estimated at appraisal. A project with higher costs than the estimated at appraisal, would have an actual return smaller than the estimated ex-ante. Analogously, if a project takes more time than planned, benefits would start being perceived in more distant periods, and the real rate of return would also be smaller than the estimated ex-ante.[21]. In this subsection we compare overrun costs and completion delay between bunching and non-bunching projects. We assume that higher overrun costs and higher completion delays are related to a lower ex-post rate of return, and therefore a lower project quality.

Table 8 displays OLS estimates for the difference in overrun costs between bunching and non-bunching projects. We use the logarithm of the ex-post cost as the dependent variable and the bunching variable as the independent one. Also, we control by the logarithm of the ex-ante cost, the logarithm of HRR-distance, and the project's delay in all the specifications. Columns (1)-(6) includes different fixed effects related to projects characteristics. Finally, columns (7) and (8) repeats specifications (5) and (6), but including a quadratic term for the variable HRR-distance. Thus, we can capture non-linear relations between the overrun costs and the the reported IRR, if any. Under theses specifications, the ratio of overrun costs between bunching and non-bunching projects would be $exp(\beta_B)$, where β_B is the coefficient of the bunching variable. In all the specifications, we are using a bandwidth of 0.5 for the bunching variable.

We find significant estimators for the bunching variable in some of the specifications (columns (2)-(6)). Estimated coefficients goes from 0.066 (std error 0.037) to 0.095 (std error 0.039). These results suggest bunched projects having overrun costs between 6.1% to 9.9% higher than non-bunched projects. However, when we control by the quadratic term of HRR-distance, results does not remain statistically significant.

We make two variations on the models previously estimated. First, we try different values of the bandwidth used to define the bunching variable. Figure 11 shows the estimated bunching coefficient with their respective 90% confidence interval of the last fours specifications (column(5)-(8)) of Table 8 using different values of the bandwidth. In none of the specifications where we control by the quadratic term, we find significant estimators for the bunching variable. Second, we consider only differences between projects with social-NPV information due to the potentially different nature of these projects, as we discussed in Section 3.3. Figure 10 displays estimated coefficients of the bunching variable for the specifications that

[20]This subsection is not replicated on the Appendix H because all projects from the ex-post evaluation sample where executed before 2020.

[21]The horizon of evaluation of all projects is 20 years and is fixed by the government.

includes the quadratic term[22] using only projects that count with social-NPV information. We find significant estimators in both specifications. Estimated coefficients are 0.11 (std error 0.047) and 0.09 (std error 0.047), suggesting that in the sample of projects without social-NPV information bunched projects have between 9.4% to 11.1% higher overrun costs.

Now we study if there is a difference on the completion delay of bunching projects. Table 9 shows OLS estimates for the difference on delay between bunching and non-bunching projects. Analogously to the case of overrun costs, we use the logarithm of ex-post duration as the dependent variable and the bunching variable as the independent one. We control by the logarithm of the ex-ante duration, HRR-distance and the logarithm of the ex-ante cost as a measure of project's size. Columns (1)-(6) includes fixed effects of projects characteristics, and column (7) and (8) includes the quadratic term for HRR-distance. The interpretation of the estimated coefficient of the bunching variable is the same as in overrun cost, but now with project delay.

We find no significant estimators for none of the specifications, suggesting no differences on delay between bunching and non-bunching projects. However, this could be due the 0.5 bandwidth used. Figure 12 shows bunching coefficient estimators for specifications (5)-(8) using different values of the bunching bandwidth. When we use a 0.3 bandwidth, we find significant estimators for the coefficient associated to the bunching variable in all the specifications. Estimated values goes from -0.362 (std error 0.134) to -0.761 (std error 0.200) ,which means that bunching projects have on average between 30.3% to 53.2% lower completion delays. These results are still valid when we use the subsample of project with social-NPV information. Figure 13 shows the estimated bunching coefficient using only these projects for different values of the bandwidth. As in the whole sample (Figure 12), we find statistically significant estimators for all the specifications when using a 0.3 bandwidth.

As we assume at the beginning of this section, higher overrun costs and/or higher delays are related to a lower ex-post rate of return (i.e, a lower ex-post quality). So far, we have presented some evidence of bunching projects having higher overrun costs and lower delays. Therefore, we can not conclude if these projects are related to a higher or lower ex-post rate of return. A possible explanation for this is that both IRR management and sequential improvements hypothesis holds. If we could identify which projects are generated under which mechanism, we should expect that those bunching projects related to IRR management exhibit a lower quality and those from sequential improvements not.

One of the predictions of the sequential improvements hypothesis[23] is that bunching projects would have more iterations. To identify projects more likely to come from optimal stopping from those more likely to come from IRR management, we split the projects according to their number of iterations. To achieve this, we assign to every project the maximum number of iterations before RS obtained on a stage[24]. Then, we define the binary variable 'high iterations' that takes the value one when a project has a number of iterations greater or equal than the median in this sample, which is 3. Otherwise, the variable is zero,

[22] Columns (7) and (8) of Table 8

[23] Tested on Section 5.1

[24] Since projects start on different stages we do not use the sum of iterations before RS through all the stages, because projects starting from early stages are more likely to have a bigger sum.

and we refer these projects as 'low iteration' ones.

Table 10 and 11 estimates the same specifications as in Table 8 and 9 but including the interaction between the bunching and high iteration variable. Therefore, $exp(\beta_B)$ is the ratio of the output (overrun costs or delay) between bunching and non-bunching projects from low iteration group, and $exp(\beta_B + \beta_{B \cdot HI})$ the ratio of the output between bunching and non-bunching projects from the high iteration group, where $\beta_{B \cdot HI}$ is the coefficient associated to the interaction variable. The last two rows of each table display $\beta_B + \beta_{B \cdot HI}$ ad its respective p-value. In all the estimations we use the projects that count with social-NPV information.

In the case of overrun costs output, we find only significant differences for projects in the low iteration group. Estimators of the coefficient associated to the bunching variable goes from 0.083 (std error 0.048) to 0.137 (std error 0.057), which means bunching projects in the low iteration group have between 8.6% to 14.6% higher overrun costs than non-bunched projects of this group. For the project's delay output we find that bunching projects from the high iteration group make less delays that non-bunching projects of the same group. Estimated coefficients goes from -0.27 (p-val 0.07) to -0.61 (p-val 0.00), meaning that bunched projects from the high iteration group make have on average 23.6% to 45.6% less delays. Additionally, in the two specifications where we control by the quadratic term oh HRR-distance (Table, Columns (6) and (8)) 11) we find significant differences for the low iteration group. Coefficients associated to the bunching variable are -0.55 (std error 0.31) and -0.78 (std error 0.35), this means that bunching projects from the low iteration group have between 42.3% to 54.1% lower delays.

To sum up, we have shown evidence of bunching projects having difference on outputs from the ex-post evaluation relative to non-bunching projects. In particular, we showed evidence that bunching projects with high number of iterations have lower completion delays and lower overrun costs. These results suggests that bunching projects with a high number of iterations are, on average, of better quality that non-bunching projects from the same group. On the other hand, our results suggest that bunching projects from the low iteration group have higher overrun costs, which is related to a lower quality. However we find some specifications where bunching projects from the low iteration group also present a lower delay. Thus, we can not conclude on direction of ex-post quality for this group of projects.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				log(ex-post cost)				
log(ex-ante cost)	0.985***	0.986***	0.989***	0.987***	0.981***	0.979***	0.981***	0.979***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)
bunching	0.047	0.066*	0.088**	0.091**	0.095**	0.083*	0.082	0.057
	(0.036)	(0.037)	(0.038)	(0.038)	(0.039)	(0.044)	(0.051)	(0.053)
log(HRR-distance)	0.005	0.006	0.014**	0.015**	0.014**	0.010	0.009	0.001
	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.014)	(0.014)
Completion delay	0.064***	0.057***	0.070***	0.072***	0.080***	0.075***	0.080***	0.075***
	(0.015)	(0.016)	(0.016)	(0.016)	(0.017)	(0.018)	(0.017)	(0.018)
log(HRR-distance)^2							0.001	0.002
							(0.003)	(0.003)
Constant	0.081	0.072	0.011	0.031	0.113	0.141	0.114	0.145
	(0.105)	(0.107)	(0.107)	(0.105)	(0.109)	(0.118)	(0.109)	(0.118)
Observations	460	455	452	451	451	425	451	425
R-squared	0.972	0.973	0.974	0.974	0.975	0.975	0.975	0.975
Year FE	No	Yes	Yes	Yes	Yes	No	Yes	No
Sector FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes
First Stage FE	No	No	No	Yes	Yes	Yes	Yes	Yes
Prep unit type FE	No	No	No	No	Yes	No	Yes	No
YearxPrerUnit type FE	No	No	No	No	No	Yes	No	Yes

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: This table shows OLS estimated for the differences on overrun costs between bunched and non-bunched projects. Overrun costs are defined as *log*(ex-post cost)-*log*(ex-ante cost). Ex-post cost it the cost of the project measured once the project has finished, ex-ante cost is the cost of the project estimated at the appraisal by the preparation unit, bunching is binary variable that takes the value one when the ex-ante rate of return of the project (IRR) is between period's hurdle rate and a 0.5 bandwidth. Delay is the logarithm of ratio between real duration of the project at the duration estimated at the appraisal.

Table 8: Overrun costs of bunching projects

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	log(observed execution time)							
log(estimated execution time)	0.484***	0.365***	0.395***	0.381***	0.444***	0.456***	0.444***	0.454***
	(0.064)	(0.068)	(0.069)	(0.069)	(0.077)	(0.088)	(0.077)	(0.088)
bunching	-0.184	-0.143	-0.187	-0.187	-0.181	-0.146	-0.291	-0.281
	(0.120)	(0.125)	(0.125)	(0.127)	(0.131)	(0.136)	(0.196)	(0.205)
log(HRR-dist)	-0.010	-0.007	-0.022	-0.027	-0.021	-0.014	-0.058	-0.059
	(0.020)	(0.021)	(0.021)	(0.021)	(0.022)	(0.022)	(0.051)	(0.056)
log(ex-ante cost)	0.173***	0.190***	0.179***	0.191***	0.192***	0.178***	0.193***	0.179***
	(0.031)	(0.030)	(0.031)	(0.031)	(0.031)	(0.035)	(0.031)	(0.035)
log(HRR-dist)^2							0.009	0.011
							(0.010)	(0.012)
Constant	-0.747**	-0.730**	-0.618*	-0.726**	-0.893**	-0.763**	-0.887**	-0.744*
	(0.337)	(0.320)	(0.332)	(0.333)	(0.345)	(0.387)	(0.347)	(0.391)
Observations	460	455	452	451	451	425	451	425
R-squared	0.373	0.436	0.455	0.463	0.473	0.500	0.474	0.501
Year FE	No	Yes	Yes	Yes	Yes	No	Yes	No
Sector FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes
First Stage FE	No	No	No	Yes	Yes	Yes	Yes	Yes
Prep unit type FE	No	No	No	No	Yes	No	Yes	No
YearxPrerUnit type FE	No	No	No	No	No	Yes	No	Yes

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: This table shows OLS estimated for the differences on delay between bunching and non-bunching projects. Delay is defined as *log*(ex-post duration)-*log*(ex-ante duration). Ex-post duration is the duration of the project measured once the project has finished, ex-ante duration is the duration of the project estimated at the appraisal by the preparation unit, bunching is binary variable that takes the value one when the ex-ante rate of return of the project (IRR) is between period's hurdle rate and a 0.5 bandwidth, ex-ante cost is project's cost measured estimated at the appraisal.

Table 9: Delay of bunching projects

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				log(ex-post cost)				
log(ex-ante cost)	0.985***	0.985***	0.990***	0.987***	0.985***	0.982***	0.985***	0.982***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.010)	(0.011)	(0.010)	(0.011)
bunching	0.083*	0.107**	0.117**	0.130**	0.137**	0.116*	0.150**	0.123*
	(0.048)	(0.054)	(0.056)	(0.053)	(0.057)	(0.062)	(0.066)	(0.071)
high iteration	0.018	0.025	0.021	0.021	0.024	0.025	0.024	0.025
	(0.022)	(0.022)	(0.022)	(0.022)	(0.023)	(0.026)	(0.023)	(0.026)
bunching·high iteration	-0.054	-0.062	-0.045	-0.063	-0.071	-0.071	-0.069	-0.070
	(0.054)	(0.060)	(0.063)	(0.060)	(0.062)	(0.066)	(0.062)	(0.066)
log(HRR-distance)	0.002	0.003	0.012*	0.012*	0.012*	0.007	0.017	0.010
	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.014)	(0.014)
Completion delay	0.067***	0.063***	0.076***	0.079***	0.082***	0.084***	0.082***	0.084***
	(0.017)	(0.018)	(0.018)	(0.018)	(0.018)	(0.020)	(0.018)	(0.020)
log(HRR-distance)^2							-0.001	-0.001
							(0.003)	(0.003)
Constant	0.076	0.071	-0.011	0.020	0.050	0.098	0.050	0.097
	(0.120)	(0.118)	(0.116)	(0.114)	(0.128)	(0.139)	(0.128)	(0.139)
Observations	397	393	390	389	389	365	389	365
R-squared	0.977	0.978	0.979	0.980	0.980	0.981	0.980	0.981
bunching + bunchingxhigh_it	0.03	0.05	0.07	0.07	0.07	0.05	0.08	0.05
p-val	0.480	0.280	0.100	0.120	0.120	0.290	0.140	0.330

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: This table shows OLS estimated for the differences on overrun costs between bunching and non-bunching projects distinguishing between high and low iterations projects. high iteration is a binary variable that takes the value one, when the projects maximum number of iterations before RS on a stage is grater or equal to the median, which is 3. The last two columns shows the sum of bunching and bunching·high iteration estimated coefficients with its p-value. The rest of the variables are the same as in Table 8. Fixed effects used are omitted due to lack of space, but are the same as the ones used Table in 8 column by column.

Table 10: Overrun costs of high and low iteration bunching projects

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	log(observed execution time)							
log(estimated execution time)	0.50***	0.37***	0.39***	0.37***	0.46***	0.47***	0.47***	0.47***
	(0.07)	(0.07)	(0.08)	(0.08)	(0.08)	(0.09)	(0.08)	(0.09)
bunching	-0.33	-0.23	-0.27	-0.35	-0.34	-0.55*	-0.51	-0.78**
	(0.28)	(0.31)	(0.29)	(0.32)	(0.33)	(0.31)	(0.36)	(0.35)
high iteration	0.01	-0.00	0.02	0.01	-0.01	-0.04	-0.01	-0.04
	(0.06)	(0.06)	(0.07)	(0.07)	(0.07)	(0.08)	(0.07)	(0.08)
bunching·high iteration	0.04	-0.04	-0.09	-0.03	-0.03	0.16	-0.03	0.17
	(0.30)	(0.32)	(0.30)	(0.33)	(0.34)	(0.32)	(0.33)	(0.31)
log(HRR-distance)	-0.00	-0.00	-0.02	-0.03	-0.02	-0.02	-0.07	-0.09*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.05)	(0.06)
log(ex-ante cost)	0.15***	0.17***	0.16***	0.17***	0.16***	0.14***	0.16***	0.13***
	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
log(HRR-distance)^2							0.01	0.02
							(0.01)	(0.01)
Constant	-0.49	-0.48	-0.30	-0.46	-0.48	-0.16	-0.46	-0.10
	(0.39)	(0.38)	(0.40)	(0.40)	(0.43)	(0.48)	(0.43)	(0.48)
Observations	397	393	390	389	389	365	389	365
R-squared	0.35	0.41	0.43	0.44	0.46	0.48	0.46	0.49
bunching + bunching·high_it	-0.290	-0.270	-0.360	-0.380	-0.370	-0.390	-0.540	-0.610
p-val	0.05	0.07	0.01	0.01	0.01	0.01	0.00	0.00

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: This table shows OLS estimated for the differences on delay between bunching and non-bunching projects distinguishing between high and low iterations projects. high iteration is a binary variable that takes the value one, when the projects maximum number of iterations before RS on a stage is grater or equal to the median, which is 3. The last two columns shows the sum of bunching and bunching·high iteration estimated coefficients with its p-value. The rest of the variables are the same as in Table 9. Fixed effects used are omitted due to lack of space, but are the same as the ones used in 9 column by column.

Table 11: Delay of high and low iteration bunching projects

6 Evidence on the dynamics of project preparation

Having established there is bunching on the ex-ante IRR distribution and that bunching is correlated to some real outcomes, here we explore how project preparation dynamics are related to IRR bunching and preparation unit's capabilities. We first look at the relation of the iterations of the "reject and resubmit" process and the distance between the hurdle rate and the reported IRR, finding that projects closer to the hurdle rate present higher iterations. Then, we test if iterations before approval and the probability of dropping a project are related to preparation unit capabilities. We find evidence of weaker units making more iterations before approval and presenting a higher ratio of dropped projects.

6.1 Project's iterations around the hurdle rate

Under sequential improvements hypothesis we expect that projects with an IRR closer to the hurdle rate have more iterations. To test this, we estimate the elasticity of the average iterations per stage respect to HRR-distance. This is different to what we did in Section 5.1 in two dimensions. First, in Section 5.1 we use only approved projects as a measure of project monitoring, here we use all the projects. This is because we want to study iterations regardless project is approved or not. Second, here we measure bunching using the variable HRR-distance, this allow us to look on the both sides around the hurdle rate, which is more related to sequential improvements than to IRR management hypothesis, where agents are targeting an specific value.

Table 12 displays OLS estimates for this elasticity. Columns (1)-(5) controls by fixed effects at preparation unit-type level and (6)-(10) uses fixed effects at the specific preparation unit level. Columns (1) and (6) uses all the projects with IRR for the the estimation while the other specifications uses only projects with both IRR and social-NPV. Columns (3)-(5) and (8)-(10) controls by log(social-NPV) as a measure of project's size. In all the specifications we control by project sector, financial source and first stage fixed effects. ‘

In the most simple specification (Column (1)) we find an estimated elasticity of -0.0137 (p-val 0.08). However, when we estimate the same specification but with fixed effects at the specific preparation unit level (column (6)), this result does not remain significant. In all the specifications we control by log(social-NPV) we find significant estimators for the elasticity of average iterations per stage respect to HRR-distance. Estimated values goes from -0.0468 (p-val 0.00) to -0.0314 (p.val 0.00). This results suggest that projects with an IRR closer to the hurdle make more iterations per stage than a projects of similar size but with an IRR farthest to the hurdle rate.

6.2 Iterations and attrition

Now we test if there are differences in project preparation between preparation units. To adress this, we use the variables defined with the project preparation sample; 'Iterations before RS' and 'Project Attrition'. Specifically, we want to address whether weaker preparation units make more iterations to obtain project approval and/or have a higher attrition rate.

6.2.1 Role of hierarchy at project preparation

We start comparing these variables at the type of organization level[25]. We assume that municipalities are weaker than ministries and firms. Thus the comparisons is between these three types of organizations.

Table 13 tests differences on iterations before RS between municipalities and firms (omitted category) and municipalities and ministries. Column (1) uses all the projects for the estimation, columns (2), (4) and (5) all the projects with IRR information, and columns (3), (6), (7) and (8) projects with both IRR and social-NPV information. In all the specifications we control by fixed effects of project sector, scope year. Iterations before RS, the dependent variable, is in logarithm. Therefore, $exp(\beta mun)$ is the ratio of iterations before RS between municipalities and firms (omitted category) and $exp(\beta mun - \beta min)$ the ratio between municipalities and ministries. Where βmun and βmin are municipalities and ministries coefficients. Additionally, in all the specifications we control by HRR-distance we estimate the elasticity of iterations before RS respect to this variable.

In all the specifications we find significant estimators for βmun. Estimated values goes from 0.194 (std error 0.061) to 0.329 (std error 0.020), thus municipalities make on average between 21.4% and 38.9% more iterations before a stage approval than firms. Then, when we compare the difference between municipalities and ministries, we also find significant estimators for all the specifications. Estimated values for $\beta mun - \beta min$ goes from 0.187 (p-val 0.00) to 0.217 (p-val 0.00), meaning that municipalities make on average between 20.5% and 24.2% more iterations before a stage approval than ministries. Finally, we only find significant estimators for the elasticity when we control by social-NPV (column (8)). In this case we estimate a elasticity of -0.016 (p-val 0.02), which means that the further is the reported IRR from the hurdle rate the less are the iterations before a stage approval.

Now we look at the differences in the attrition rate. Table 14 estimates the difference in the attrition ratio between municipalities and firms and municipalities and ministries. All specifications includes project sector, project scope, year, stage and total iterations fixed effects. While iterations before RS is a variable at project-stage level, attrition is at project level, therefore, year and stage fixed effects are discomposed in two; one for the first year (stage) and one for the last year (stage) observed. Column (1) uses all the projects for the estimation, columns (2), (4) and (5) all the projects with only IRR information, and columns (3), (6), (7) and (8) projects with both IRR and social-NPV information. In all the specifications, βmun is the difference in the attrition rate between municipalities and firms and $\beta mun - \beta min$ the difference between municipalities and ministries, this difference is calculated in the last two lines with its respective p-value.

We find significant differences both between municipalities with firms and municipalities with ministries through all specifications. The estimated municipality coefficient (βmun), which is 99% significant in all the specifications, goes from 0.096 (std error 0.029) to 0.172

[25]Ministry, municipality, firms, and other units

(std error 0.011), meaning that municipalities have an attrition rate that is between 9.6 and 17.2 percentage points higher. In the difference between municipality and ministry coefficients, we also find 99% significant estimates in all the specifications. Differences go from 0.06 (p-val 0.00) to 0.09 (p-val 0.00), meaning that municipalities have an attrition rate of 6 to 9 percentage points higher than ministries.

6.2.2 Project preparation capacity

Finally, we want to test if units with the same hierarchy but with different capacities exhibit differences on iterations before RS and/or on the attrition rate. To address this, we use two measures of municipality capabilities. The first one, is the annual budget of the municipality, which we can think as a measure of size[26]. The second measure, is the percentage of the staff who counts with a professional degree ($prof$). We use this variable as a measure of the sophistication of the preparation unit.

Table 15 and 16 tests differences in iterations before RS and attrition across municipalities. In all specifications, we control by project sector, project scope, municipality region, stage year, and specific stage fixed effects. Columns (1)-(3) uses all projects prepared by municipalities in the project preparation sample, column (4) projects that count with IRR information and columns (5)-(7), the sub-sample of projects with both IRR and social-NPV. In the case of iterations before RS, the last two rows shows the estimated elasticity of this variable respect to HRR-distance.

In the case of iterations before RS, we find significant and negative coefficients for log(budget) when we use the whole sample (columns (1) and (3)). Both estimated coefficients are -0.03 (std error 0.01), suggesting that municipalities with lower budget are related with more number of iterations before a project's stage approval. When we use the sub-sample of projects with IRR or social-NPV information (columns (2)-(7)) coefficients are all negative and significant except when we control by the quadratic term of HRR-distance (column (7)). In the case of log(prof) we only find significant estimators in the whole sample and in projects with IRR. In this cases, estimated coefficients goes from -0.04 (std error 0.02) to -0.08 (std error 0.03). However when we use the sample of projects with IRR and social-NPV information estimated coefficients are no longer significant. Finally, the estimated elasticity is not significant for none of the specifications.

In the case of attrition rate we on only find significant estmators for the log(prof) variable when we use both projects with on ly IRR and projects with IRR and social-NPV information. In this cases estimated coefficients goes from 0.03 (std error 0.01) to 0.05 (0.01) suggesting that municipalities with higher percentage of professional staff tend to quit more projects.

[26]The correlation between annual budget and population is approximately 0.935

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES					log(total iterations)					
log(HRR-dist)	-0.014*	-0.013	-0.041***	-0.035***	-0.023*	-0.012	-0.014	-0.045***	-0.047***	-0.040**
	(0.008)	(0.009)	(0.009)	(0.010)	(0.013)	(0.009)	(0.010)	(0.011)	(0.014)	(0.019)
log(social-NPV)			0.040***	0.038***	0.037***			0.043***	0.051***	0.051***
			(0.005)	(0.005)	(0.005)			(0.006)	(0.008)	(0.008)
$log(\text{HRR-dist})^2$					-0.004					-0.003
					(0.003)					(0.005)
log(n-stages)	1.408***	1.331***	1.298***	1.318***	1.317***	1.379***	1.316***	1.289***	1.285***	1.283***
	(0.045)	(0.047)	(0.047)	(0.051)	(0.051)	(0.048)	(0.051)	(0.051)	(0.067)	(0.068)
Constant	1.302***	1.329***	0.857***	0.878***	0.883***	1.307***	1.334***	0.825***	0.708***	0.712***
	(0.020)	(0.022)	(0.064)	(0.067)	(0.068)	(0.021)	(0.023)	(0.077)	(0.104)	(0.104)
Observations	3,559	3,009	3,009	2,970	2,970	3,393	2,849	2,849	2,205	2,205
R-squared	0.338	0.354	0.370	0.417	0.417	0.421	0.438	0.450	0.570	0.570
Projects	All	NPV	NPV	NPV	NPV	All	NPV	NPV	NPV	NPV
Preparation unit type FE	Yes	Yes	Yes	No	No	No	No	No	No	No
Year FE	Yes	Yes	Yes	No	No	Yes	Yes	Yes	Yes	Yes
Year x Prep Unit type FE	No	No	No	Yes	Yes	No	No	No	No	No
Preparation Unit FE	No	No	No	No	No	Yes	Yes	Yes	No	No
Prep Unit x Year	No	No	No	No	No	No	No	No	Yes	Yes
elasticity	-0.0137	-0.0129	-0.0410	-0.0347	-0.0314	-0.0125	-0.0140	-0.0452	-0.0468	-0.0453
p-val	0.08	0.13	0.00	0.00	0.00	0.15	0.15	0.00	0.00	0.00

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: This table reports OLS estimates for the elasticity of average iterations per stage with respect to HRR-distance. Total iterations is the sum of iterations that a project makes through all the stages that applies to, HRR-distance is the distance between the ex-ante IRR and period's hurdle rate of a project, social-NPV is the social net present value estimated by the preparation unit at the appraisal, and n-stages is the total number of stages that the project applies to. The row projects indicates the sample of projects used, 'All' refers to projects with IRR and not necessarily social-NPV and 'NPV' projects with IRR and social-NPV information. The last two rows displays the estimated elasticity and its respective p-value. In all the estimations we control by project sector, financial source and first stage fixed effects.

Table 12: Average iterations per stage and distance between reported IRR and the hurdle rate.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES				*log*(iterations before RS)				
Ministry	0.116***	0.033	-0.017	0.028	0.029	-0.021	-0.019	-0.029
	(0.019)	(0.052)	(0.056)	(0.052)	(0.053)	(0.057)	(0.057)	(0.056)
Municipality	0.329***	0.222***	0.200***	0.215***	0.216***	0.194***	0.197***	0.199***
	(0.020)	(0.056)	(0.060)	(0.056)	(0.056)	(0.061)	(0.061)	(0.060)
Other	0.228***	0.083	0.070	0.079	0.080	0.067	0.068	0.080
	(0.031)	(0.102)	(0.110)	(0.102)	(0.102)	(0.110)	(0.110)	(0.110)
$log(HRR\text{-distance})$				-0.008*	-0.005	-0.009	-0.001	-0.015*
				(0.005)	(0.008)	(0.005)	(0.008)	(0.008)
$log(HRR\text{-distance})^2$					-0.001		-0.001	-0.000
					(0.001)		(0.001)	(0.001)
log(social-NPV)								0.019***
								(0.004)
Constant	0.774***	0.821***	0.872***	0.841***	0.837***	0.891***	0.885***	0.665***
	(0.018)	(0.050)	(0.054)	(0.052)	(0.053)	(0.056)	(0.057)	(0.070)
Observations	19,635	2,970	2,575	2,970	2,970	2,575	2,575	2,575
R-squared	0.107	0.143	0.166	0.144	0.144	0.167	0.168	0.176
Sample	All	IRR	NPV	IRR	IRR	NPV	NPV	NPV
Municipalidad - Ministerio = 0	0.213	0.189	0.217	0.187	0.187	0.215	0.216	0.228
p-val	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Elasticity				-0.008	-0.006	-0.009	-0.004	-0.016
p-val				0.09	0.3	0.11	0.57	0.02

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: This table reports OLS estimates for differences on iterations before RS between different types of organizations. Firms is the omitted category. In the Sample row, 'All' refers to all projects in the project preparation sample,'IRR' refers to projects with IRR and not necessarily social-NPV and 'NPV' projects with IRR and social-NPV. All specifications includes project sector, scope and year fixed effects. The row 'Municipality - Ministry' displays differences of 'Municipality' and 'Ministry' estimated coefficients. The last two rows displays the estimated elasticity of iterations before RS respect to HRR-distance.

Table 13: Differences on iterations before approval between different type of organizations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Attrition							
Ministry	0.078***	0.048*	0.037	0.054**	0.052**	0.042	0.038	0.038
	(0.011)	(0.025)	(0.027)	(0.025)	(0.025)	(0.027)	(0.027)	(0.027)
Municipality	0.172***	0.121***	0.095***	0.127***	0.123***	0.100***	0.096***	0.097***
	(0.011)	(0.027)	(0.029)	(0.028)	(0.028)	(0.029)	(0.029)	(0.029)
Other	0.120***	0.114**	0.128**	0.116**	0.114**	0.132**	0.130**	0.132**
	(0.015)	(0.051)	(0.059)	(0.051)	(0.051)	(0.058)	(0.058)	(0.058)
log(social-NPV)								0.002
								(0.002)
$log(HRR$-distance)				0.012***	-0.003	0.014***	-0.001	-0.003
				(0.003)	(0.004)	(0.004)	(0.005)	(0.005)
$log(HRR$-distance$)^2$					0.002***		0.002***	0.002***
					(0.001)		(0.001)	(0.001)
Constant	0.138***	0.102***	0.091***	0.069***	0.088***	0.057**	0.075***	0.049
	(0.010)	(0.024)	(0.026)	(0.025)	(0.025)	(0.027)	(0.026)	(0.037)
Observations	28,149	3,811	3,151	3,811	3,811	3,151	3,151	3,151
R-squared	0.464	0.347	0.313	0.352	0.354	0.318	0.320	0.321
Sample	All	IRR	NPV	IRR	IRR	NPV	NPV	NPV
Municipalidad - Ministerio = 0	0.09	0.07	0.06	0.07	0.07	0.06	0.06	0.06
p-val	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: This table reports OLS estimates for differences on Attrition rate between different types of organizations: ministries, municipalities, firms (omitted category) and other organizations. In the sample row ,'All' refers to all projects in the project preparation sample,'IRR' refers to projects with IRR and not necessarily social-NPV and 'NPV' projects with IRR and social-NPV information. All specifications includes project sector, scope, first year(stage), last year(stage) and total iterations fixed effects. The row 'Municipality - Ministry' displays differences of 'Municipality' and 'Ministry' estimated coefficients with its respective p-value.

Table 14: Differences on attrition ratio between different type of organizations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES				*log*(iterations before RS)			
log(budget)	-0.03***		-0.03***	-0.06**	-0.04*	-0.04*	-0.04
	(0.01)		(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
log(prof)		-0.04*	-0.05***	-0.08**	-0.04	-0.03	-0.03
		(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)
log(social-NPV)						0.01	0.01
						(0.01)	(0.01)
log(HRR-distance)						-0.02	-0.01
						(0.02)	(0.02)
log(HRR-distance)^2							-0.00
							(0.01)
Constant	1.54***	1.22***	1.78***	2.21***	1.85***	1.73***	1.69***
	(0.12)	(0.06)	(0.15)	(0.39)	(0.40)	(0.41)	(0.42)
Observations	7,796	7,840	7,789	743	640	640	640
R-squared	0.13	0.13	0.13	0.18	0.24	0.24	0.24
Sample	All	All	All	IRR	NPV	NPV	NPV
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Scope FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stage FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
elasticity						-0.017	-0.018
p-val						0.29	0.28

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: This table reports OLS estimates for differences on *log*(iterations before RS) between municipalities. Budget correspond to yearly budget of the municipality measured on fixed year, prof is the percentage of professional staff who works in the municipality, also on a fixed year. Social-NPV and IRR are the social net present value ant the rate of return of the project estimated by the municipality at the appraisal. In the sample row, 'All' refers to all approved project stages prepared by municipalities, 'IRR' refers to projects with IRR and not necessarily social-NPV and 'NPV' projects with IRR and social-NPV information. The last two rows displays the estimated elasticity of iterations before RS respect to HRR-distance and its p-value.

Table 15: Differences on iterations before approval between municipalities

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES				Attrition			
log(budget)	-0.00		-0.00	0.01	0.01	0.00	0.00
	(0.00)		(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
log(prof)		-0.00	-0.00	0.03**	0.05***	0.04***	0.04***
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
log(social-NPV)						-0.01	-0.01
						(0.01)	(0.01)
log(HRR-distance)						0.02**	0.02*
						(0.01)	(0.01)
$log(\text{HRR-distance})^2$							0.00
							(0.00)
Constant	0.35***	0.34***	0.37***	-0.08	-0.07	0.04	0.04
	(0.05)	(0.03)	(0.06)	(0.18)	(0.19)	(0.20)	(0.20)
Observations	13,388	13,459	13,370	1,089	891	890	891
R-squared	0.49	0.49	0.49	0.49	0.43	0.44	0.44
Sample	All	All	All	IRR	NPV	NPV	NPV
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Scope FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stage FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: This table reports OLS estimates for differences on the attrition rate between municipalities. Budget correspond to yearly budget of the municipality measured on fixed year, prof is the percentage of professional staff who works in the municipality, also on a fixed year. Social-NPV and IRR are the social net present value ant the rate of return of the project estimated by the municipality at the appraisal. In the sample row, 'All' refers to all approved project stages prepared by municipalities, 'IRR' refers to projects with IRR and not necessarily social-NPV and 'NPV' projects with IRR and social-NPV information. The last two rows displays the estimated elasticity of iterations before RS respect to HRR-distance and its p-value.

Table 16: Differences on attrition ratio between municipalities

7 Results discussion

Previous sections have shown the following stylized facts. First is the existence of bunching just above both current and prior period's hurdle rates. Second, bunching projects with low iterations on the preparation process relates to higher overrun costs, and those with high iterations relates to lower completion delays. Third, projects with a reported IRR around the hurdle rate are related to higher average iterations per stage and higher iterations before a stage approval. Finally, preparation units with higher hierarchy, which we assume have proxies for stronger project preparation capacity, exhibit lower iterations before a stage approval and a lower probability of dropping a project. Table 17 summarizes the principal results shown through the paper.

Both the IRR management and sequential improvements hypothesis predicts bunching on the ex-ante IRR distribution. The only difference is that under IRR management, we expect to observe bunching above current and previous hurdle rates while under sequential improvements only over the current hurdle rate. In Section 4 we show evidence of bunching above current and previous hurdle rates. With this evidence, we can not reject neither IRR management nor the sequential improvements hypothesis because both may be generating the observed data. However, this evidence led us to move from the traditional approach favoring a strategic approach on project preparation.

Concerning the project's quality, the IRR management hypothesis predicts that bunching projects should be of the low-quality type. While sequential improvements hypothesis predicts bunching projects should be of the high-quality type. In Section 5.2 we use overrun costs and completion delays outputs as proxies for project's quality. We first find some evidence of bunching projects having higher overrun costs (related to low-quality type) and lower completion delays (related to high-quality type). However, the difference on completion delays looks more like a statistic singularity than an evidence of a systematic difference. If the case, bunching projects tend to present higher overrun costs ,and therefore a lower quality. . Then we split projects according to their number of total iterations, finding that bunching projects with low iterations exhibit higher overrun costs. However, for some of the specifications these projects also exhibit lower completion delays. On the other hand, bunching projects with high iterations exhibit lower completion delays and no difference in overrun costs. In other words, these results suggests that bunching projects from the high iteration group are of the high-quality type and is not possible to conclude the direction of the quality type of projects from low iteration group, besides the results showing higher overrun costs of bunching projects on this group.

Finally, we explore the dynamics of project preparation. Consistently with the sequential improvements hypothesis, we find evidence of projects with a rate of return closer to the hurdle rate are related to higher average iterations per stage and higher iterations before a stage approval on the reject and resubmit process. Then we analyze the difference in the number of iterations before a stage approval and the probability of dropping a project between different types of preparation units. We start comparing preparation units at the type of organization level. We find that municipalities, which we assume are weaker than ministries and state owned firms, on average make more iterations before a stage approval and have a higher ratio of abandoned projects. Then we compare these two variables across municipalities using the annual budget and percentage of professional staff as proxies for the municipality's capacities. We find a negative correlation between the iterations before a stage approval and the two capacities proxies used. However, results do not remain significant when we control by social-NPV and HRR-distance. In the case of dropped projects, we only find significant results when using the sub-sample of projects evaluated with cost-benefit analysis (i.e at least with information about IRR). Municipalities with a higher percentage of professional staff drop more projects. A possible explanation for this is that the higher the percentage of professional staff, the higher the number of projects presented. Therefore, the higher the probability of dropping a project, due to restriction on execution capacity.

8 Concluding Remarks

Through this paper we have analyzed project data to address the question if there is evidence for project preparation agents acting strategically. We have shown evidence of bunching on the ex-ante IRR distribution, difference on project quality between bunching and non-bunching projects and heterogeneity in the project preparation process in different types of preparation units. Overall, this results lend some support on the hypothesis that agents preparing projects face agency problems, which induce a strategic behavior. However, we can not reject none of the two hypothesis developed under strategic approach. In the case of IRR management hypothesis we find bunching of projects above hurdle rates used on previous periods. This results is not consistent with sequential improvements approach. On the other hand and consistently with sequential improvements, we showed some evidence of bunching project from the high-iteration group being of the high-quality type.

Although the results shown in this paper does not establish causality we shed some light on the importance of project preparation. In particular, results suggest that the interaction between the agent who prepares the project and the principal who decides on the approval could be important on the correct formulation and execution of projects. This is an interesting topic for future research. In particular further research should investigate the external validity of these results by extending the analysis to project data from other type of organizations or countries. Another promising line of research is to add new data sources for current project data. For example, it would be interesting to use project appraisal reports to measure new features of projects.

Empirical implications	**Traditional Approach**	IRR **Management**	**Sequential Improvements**	**Findings**
(i) Bunching of projects above period's HRR	No	Yes	Yes	Evidence in favour of IRR Management and Sequential improvemnts hypothesis (Figure 4, Tables 4 and 5).
(ii) Change in the HRR generates bunching above the new cutoff	No	Yes	Yes	Evidence in favour of IRR Management and Sequential improvemnts hypothesis (Figure 4, Tables 4 and 5)
(iii) Bunching of projects above previous cutoffs	No	Yes	No	Evidence in favour of IRR management hypothesis (Figure 4 and Table 5).
(iv) Bunching projects characteristics	-	Projects with a lower probability of being monitored	-	Evidence against IRR managment hypothesis (Table 6).

(v) Project quality	-	Low-quality type	High-quality type	Mixed results. Evidence of bunching projects having higher overrun costs and lower completion delays (Tables 8, 9 and Figure 12), and bunching projects with high iterations having lower completion delays and no difference on overrun costs, which is related to high quality (Tables 10 and 11).
(vi) Iterations before getting a project approved	-	-	More on weaker units	Evidence in favour of sequential improvements hypothesis. Municipalities make more iterations before approval than ministries and state owned firms (Table 13).
(vii) Aborted projects	-	-	More on weaker units	Evidence in favour of sequential improvements hypothesis. Municipalities quit more projects than ministries and state owned firms (Table 14).
(viii) Projects closer to the HRR	-	-	Projects with more iterations	Evidence in favour of sequential improvements hypothesis. Negative elasticity of average iterations per stage relative to HRR-distance (Tables 7 and 12).

Notes: This tables replicates Table 1 including a summary of the main results for each empirical implication.

Table 17: Summary of results

A Model examples

A.1 Naive CFO model

Consider a Chief Financial Officer (CFO) who is the principal and wants to invest the organization's resources in the projects with the highest possible rate of return R_i. The distribution of R_i in the population, $G(R_i)$, is common knowledge but the exact value R_i is unknown to the CFO. In contrast, the agent in charge of the project preparation does observe the true return R_i. Nonetheless, she has the option to report to the CFO a different rate of return. The agent does get some extra utility αA_i if project i is approved by the CFO (so the dummy variable A_i takes the value one when approved and zero otherwise). Still, the agent suffers a cost for misreporting given by $c(\tilde{R}_i - R_i)$ that is increasing and convex in the magnitude of the misreporting $\tilde{R}_i - R_i$. Formally, the agent's problem is choosing the reported rate of return $\tilde{R}_i$ such that solves

$$\max_{\tilde{R}_i} \quad \alpha A_i - c(\tilde{R}_i - R_i) \tag{6}$$

Noting that α is the utility weight of the agent given to the approval. An agent with $\alpha = 0$ means that the agent does not privately care about the execution of the project, as in the the standard case without any agency problems. The larger α, the larger the agent's private gains from having the project approved. The timing of the events is as follows, without any time discounting for simplicity. First the CFO pre-announces the hurdle rate cutoff r and an approval rule for A. After the announcement, agents report $\tilde{R}_i$. Immediately after the CFO carries out projects according to the previously announced rule.

Equilibrium with a Naive CFO pre-announcing a rate

A naive CFO would implement an approval rule such that, first, the hurdle rate coincides with the cost of capital r and, second, the decision rule is based on the reported value using a step function, so $A(\tilde{R}_i, r) = 1[\tilde{R}_i > r]$, without any consideration to the incentive compatibility of the agent. The optimal behavior for the agent is to truthfully reveal R_i when $R_i > r$; because there is not point at suffering a utility loss for misreporting. When R_i is too small it is also a dominant strategy to tell the truth in this model. But for an intermediate range there is an incentive for misreporting, namely when R_i is between $\widehat{R}$ and r, because their cost of misreporting is overcome by the gains from project execution.

A.2 Sequential improvements model

We consider a sequential game with 2 players; Nature and an Agent. The game has the following structure:

- **Stage 0:** Nature generates a perceived rate of return IRR_0.
- **Stage 1:** The Agent observes IRR_0 and submits the project. If $IRR_0 \geq HRR$, the project is accepted and the game ends. On the contrary, if $IRR_0 < HRR$, project

is rejected and the agent decides whether to quit the project, and the game ends, or make a costly re-evaluation and advance to the next stage. The re-evaluation generates IRR_1 that with probability p is an improvement, such that $IRR_1 > IRR_0$, and with probability $1-p$ has no effect and $IRR_1 = IRR_0$.

- **Stage 2:** The Agent observes IRR_1 and submits the project. If $IRR_1 \geq HRR$, the project is accepted and the game ends. On the contrary, if $IRR_1 < HRR$, project is rejected and the agent decides whether to quit the project, and the game ends, or make a costly re-evaluation and advance to the next stage. The re-evaluation generates IRR_2 that with probability p is an improvement, such that $IRR_2 > IRR_1$, and with probability $1-p$ has no effect and $IRR_2 = IRR_1$.

- **Stage k:** The Agent observes IRR_{k-1} and submits the project. If $IRR_{k-1} \geq HRR$, the project is accepted and the game ends. On the contrary, if $IRR_{k-1} < HRR$, project is rejected and the agent decides whether to quit the project, and the game ends, or make a costly re-evaluation and advance to the next stage. The re-evaluation generates IRR_k that with probability p is an improvement, such that $IRR_k > IRR_{k-1}$, and with probability $1-p$ has no effect and $IRR_k = IRR_{k-1}$.

B List of variables

Economic evaluation data	
Variable	**Description**
Project Code	Code that identifies the project.
IRR	Social internal rate of return of the project. Calculated by the prepartion unit.
Social-NPV	Social net present value of the prject. Calculated by the preparation unit.
Project preparation data	
Variable	**Description**
Project Code	Code that identifies the project.
Year	Current year
Stage	Stage the project is applying in the current year
RATE	Output of the evaluation developed by the MDSF in the current year.
Iterations	Iterations between the preparation unit and the MDSF during the year.
Preparation Unit	Unit in charge of the project.
Type or organization	Municipality, Ministry , Firm or Others.
Scope	Reach of the project (comunal, provincial, regional, etc.)
Ex-post evaluation data	
Variable	**Description**
Project Code	Code that identifies the project.
Cost ex-ante	Cost of the project estimated at appraisal.
Cost ex-post	Real cost of the project measured after the execution.
Estimated execution time	Duration project's execution estimated at appraisal.
Observed execution time	Real duration of the project's execution measured after the execution was finished.

Notes: This table describes the list of variables contained on the three data samples mentioned on Section 3.2

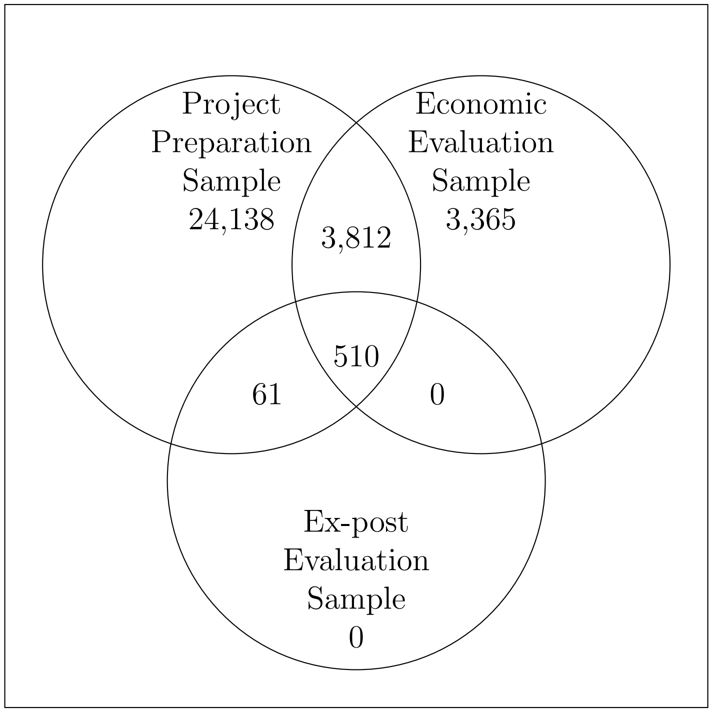
Table 18: Variables description

C Concentration of projects without social-NPV

Year	Concentration of projects without social-NPV
1997	0,10%
1998	0,70%
1999	0,40%
2000	0,50%
2001	0,65%
2002	1,80%
2003	2,30%
2004	6,66%
2005	6,26%
2006	5,21%
2007	6,31%
2008	5,61%
2009	5,61%
2010	9,51%
2011	10,87%
2012	4,96%
2013	3,66%
2014	2,95%
2015	5,56%
2016	6,61%
2017	5,51%
2018	2,20%
2019	2,95%
2020	2,35%
2021	0,75%
Total	**100%**

Notes: This table

Table 19: Summary statistics



Notes: This figure shows the intersection between the 3 data samples mentioned in Section 3.2.

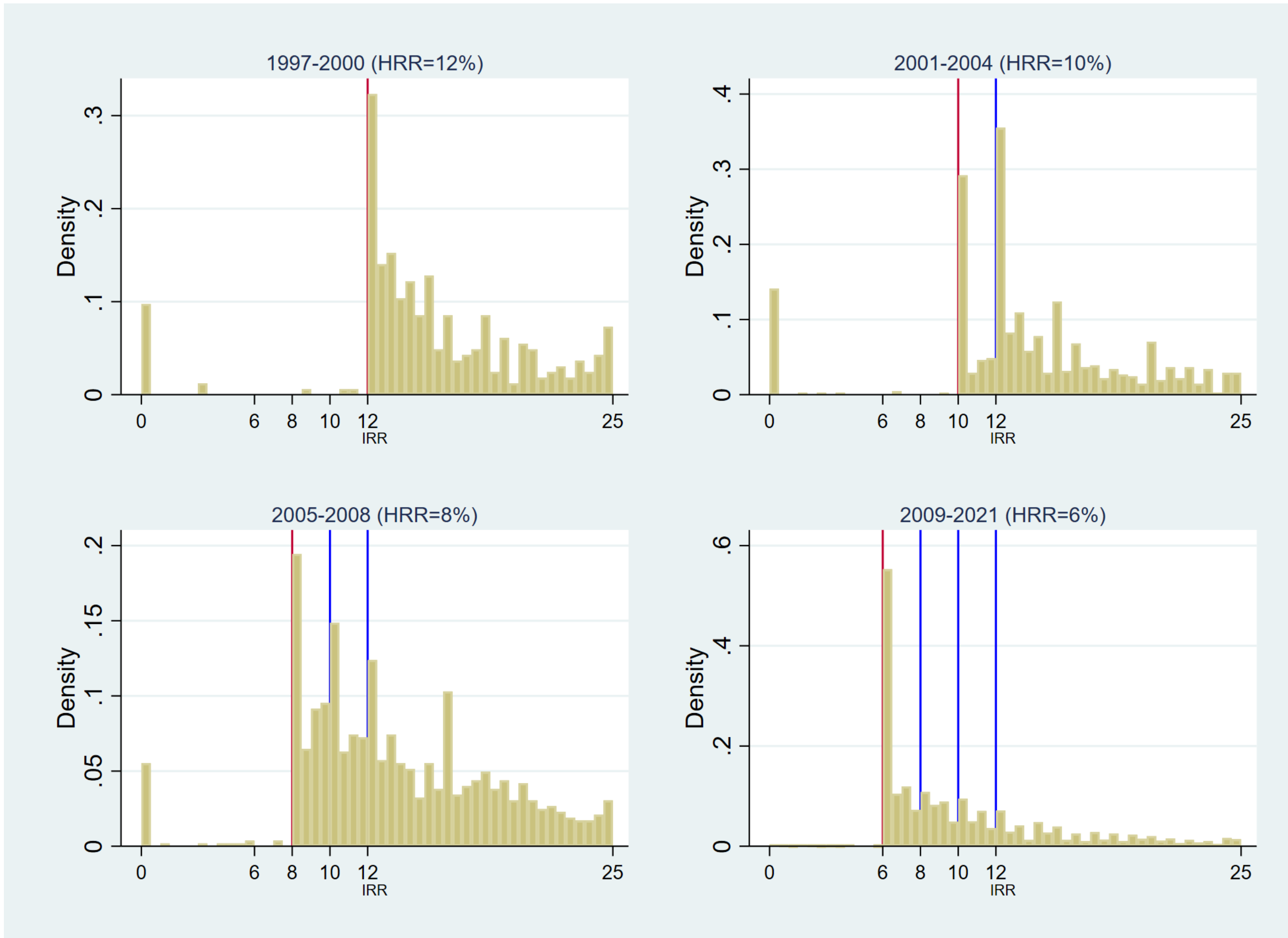
Figure 7: Data Overlap

Preparation unit type	**Number of projects**	**Percentage**	**Cumulative**
MUNICIPALITY	1,405	30.17	30.2
DOH	731	15.7	45.9
MINVU	655	14.06	59.9
MOP	589	12.65	72.6
DIRECCION VIALIDAD	498	10.69	83.3
DOP	193	4.14	87.4
EMPRESA	173	3.71	91.1
OTROS	145	3.11	94.2
SECTRA	84	1.8	96.0
METRO	62	1.33	97.4
GOB REG	38	0.82	98.2
CNR	37	0.79	99.0
MIN TRANSPORTE	25	0.54	99.5
DOA	15	0.32	99.8
MINJU	4	0.09	99.9
SAG	3	0.06	100.0
Total	**4,657**	**100**	

Notes: This table describes types of preparation units identified in the economic evaluation sample.

Table 20: Preparation uniy type categorios

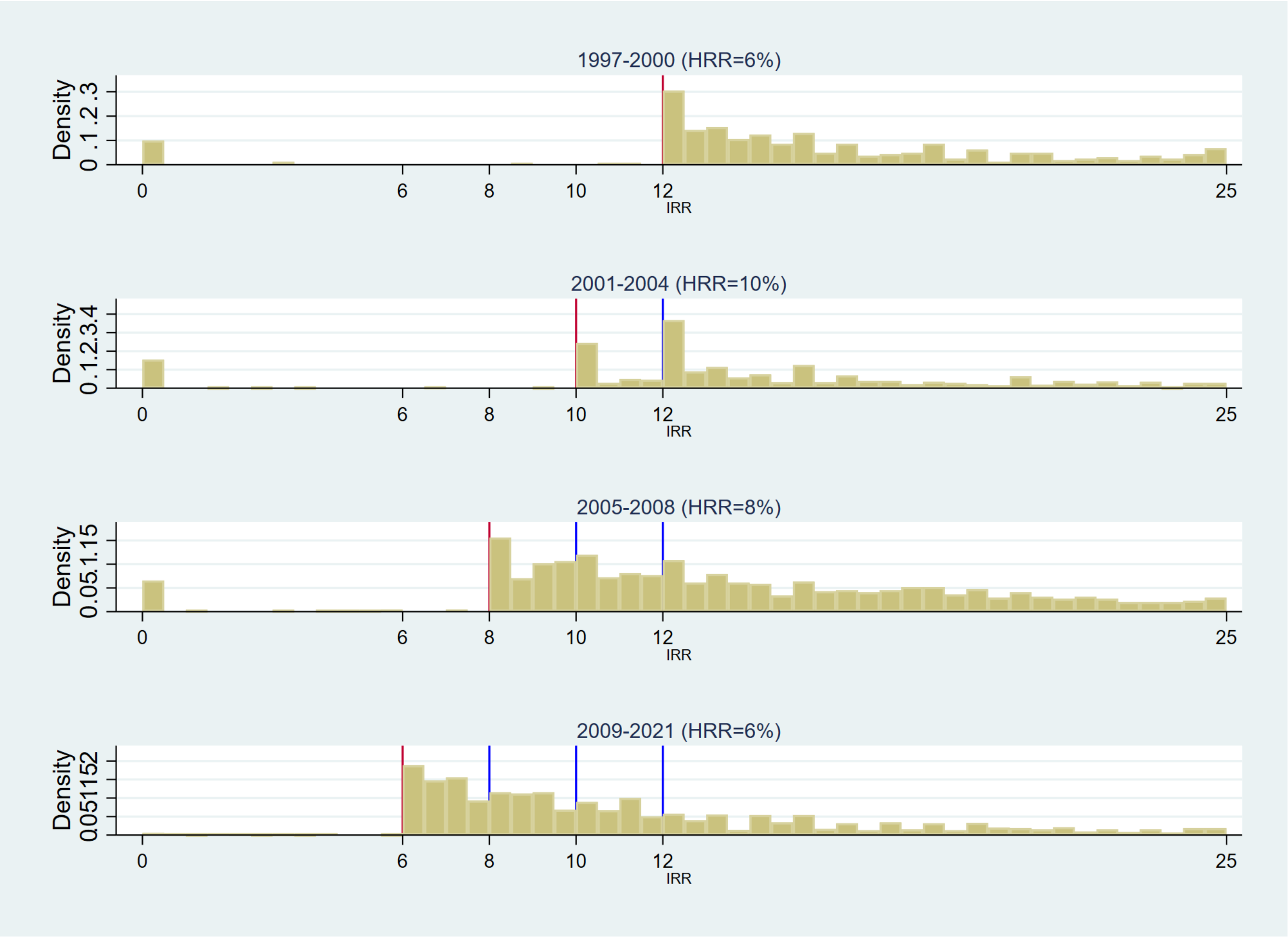
D IRR distribution by period



Notes: This figure depicts the distribution of the ex-ante IRR in the periods defined by the different hurdle rates used. Red lines correspond to the period's hurdle rate and blue lines a previous period's hurdle rates.

Figure 8: ex-ante IRR distribution by HRR-period

E IRR distribution of projects with NPV information



Notes: This figure depicts the distribution of the ex-ante IRR in the periods defined by the different hurdle rates used. Red lines correspond to the period's hurdle rate and blue lines a previous period's hurdle rates.

Figure 9: ex-ante IRR distribution by HRR-period

F Polynomials estimated

F.1 Basic polynomial

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES				Percentage of projects				
γ_6				0.225***				0.219***
				(0.003)				(0.005)
γ_8			0.061***	0.035***			0.057***	0.030***
			(0.002)	(0.002)			(0.003)	(0.004)
γ_{10}		0.102***	0.044***	0.029***		0.098***	0.040***	0.025***
		(0.002)	(0.002)	(0.002)		(0.003)	(0.002)	(0.003)
γ_{12}	0.108***	0.128***	0.034***	0.020***	0.103***	0.124***	0.031***	0.016***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)
Constant	0.003	0.009	0.009**	0.014***	0.009*	0.011*	0.013**	0.020***
	(0.004)	(0.007)	(0.004)	(0.004)	(0.005)	(0.006)	(0.005)	(0.007)
Observations	160	160	160	160	160	160	160	160
R-squared	0.592	0.742	0.663	0.897	0.629	0.757	0.684	0.911
Hurdle rate	12	10	8	6	12	10	8	6
Integer FE	No	No	No	No	Yes	Yes	Yes	Yes
Period	1997-2000	2001-2004	2005-2008	2009-2021	1997-2000	2001-2004	2005-2008	2009-2021

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: This table reports OLS estimates for 5-degree polynomial.Periods are defined by the different hurdle rates used. The γ_i variables are binary variables that takes tha value 1 when the bin $[j, (j+0.5)\%)$ contains i. Columns (5)-(8) includes a fixed effects for bins that has an integer number as a lower bound.

Table 21: OLS estimations for the basic polynomial

F.2 Polynomial with structural break

	(1)	(2)	(3)	(4)
VARIABLES		Percentage of projects		
γ_6				0.201***
				(0.003)
γ_8			0.040***	0.016***
			(0.002)	(0.003)
γ_{10}		0.084***	0.027***	0.014***
		(0.004)	(0.002)	(0.002)
γ_{12}	0.079***	0.113***	0.021***	0.008***
	(0.004)	(0.003)	(0.001)	(0.002)
Constant	0.020*	0.051**	0.031**	0.002
	(0.011)	(0.025)	(0.013)	(0.004)
Observations	160	160	160	160
R-squared	0.877	0.891	0.926	0.975
Hurdle rate	12	10	8	6
Integer FE	Yes	Yes	Yes	Yes
Period	1997-2000	2001-2004	2005-2008	2009-2021

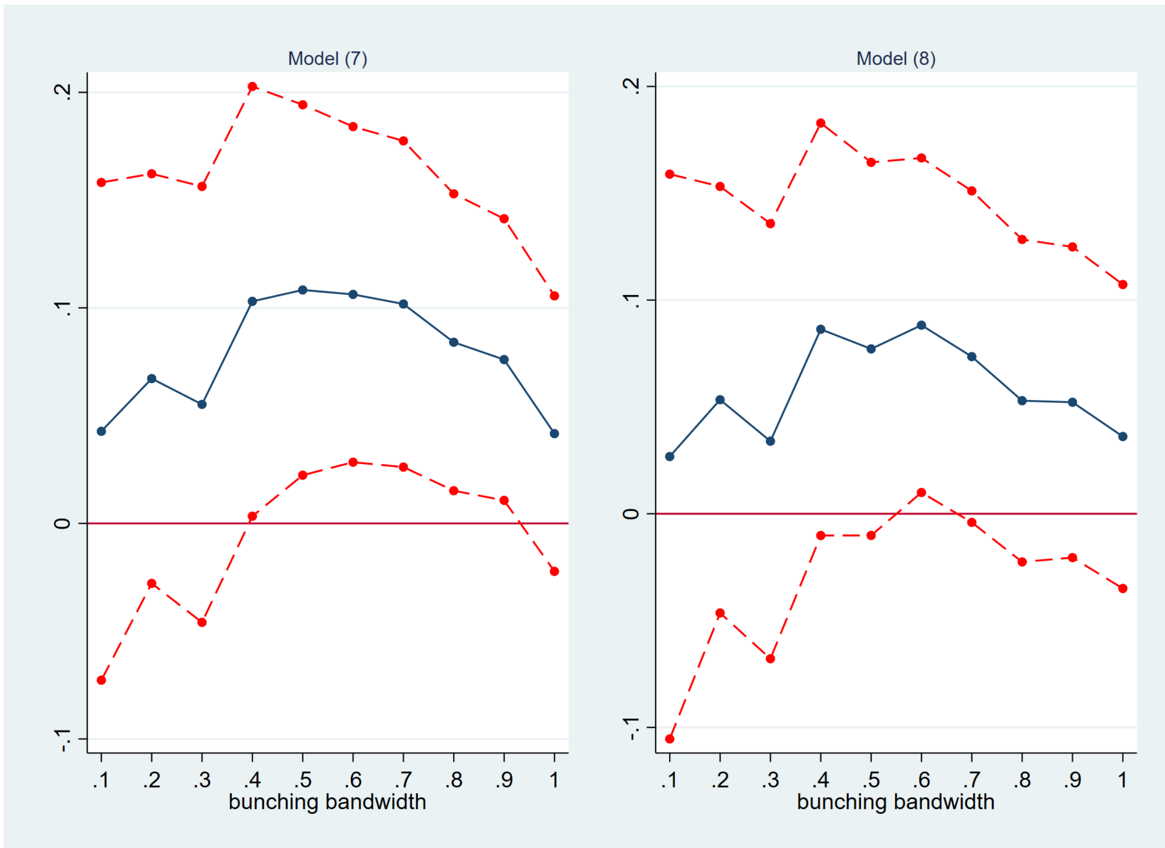
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: This table reports OLS estimates for a 3-degree polynomial.Periods are defined by the different hurdle rates used. The γ_i variables are binary variables that takes tha value 1 when the bin $[j, (j+0.5)\%)$ contains i. All the specifications includes a fixed effects for bins that has an integer number as a lower bound.

Table 22: OLS estimations for the polynomial with structural break

G Bunching coefficient with different bandwidths

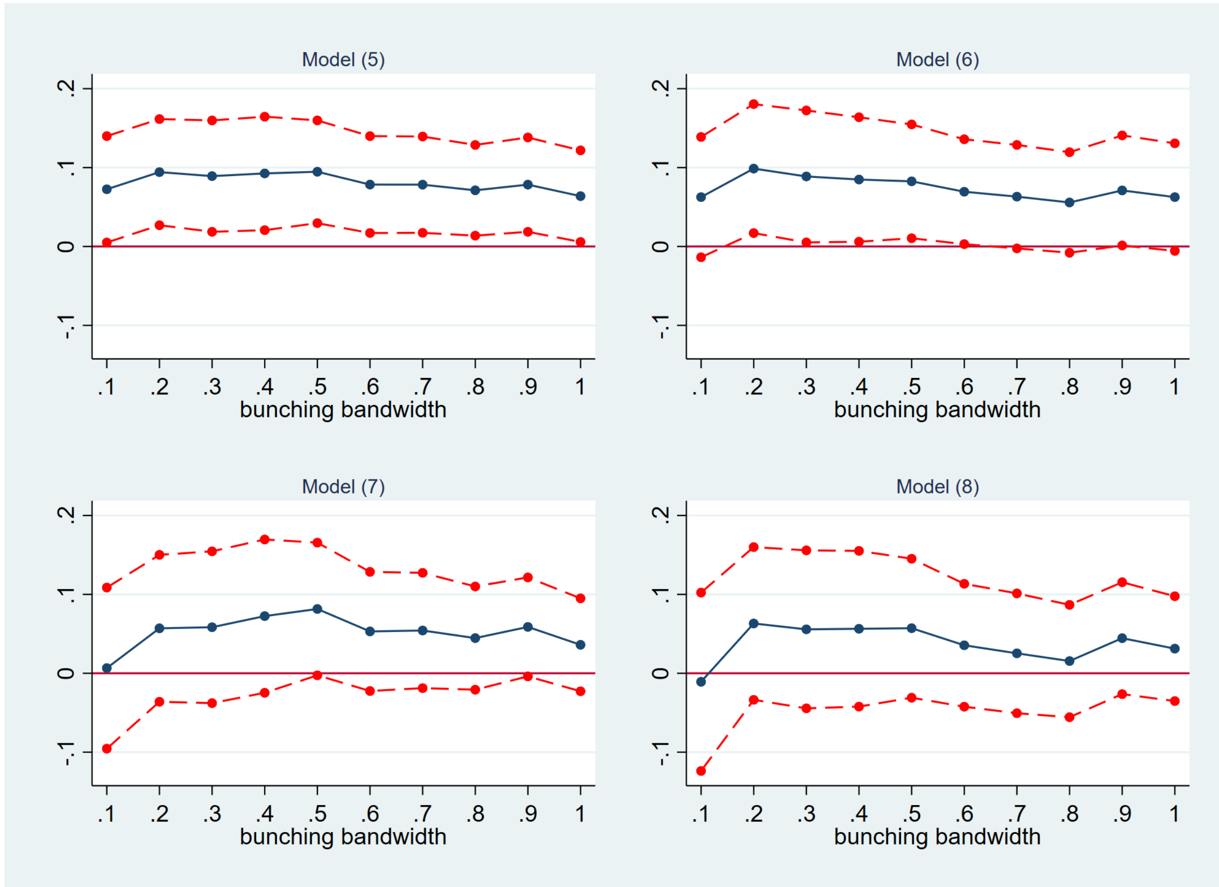
G.1 Bunching coefficient estimator for projects with social-NPV information



Notes: This figure shows estimated coefficient for the bunching variable using specifications (7) and (8) of Table 8 but considering only projects with social-NPV information. Blue dorts represent the estimated coefficient and red dots a 90% confidence interval for this coefficient.

Figure 10: Bunching coefficient estimator using different values of the bandwidth for projects with social-NPV information.

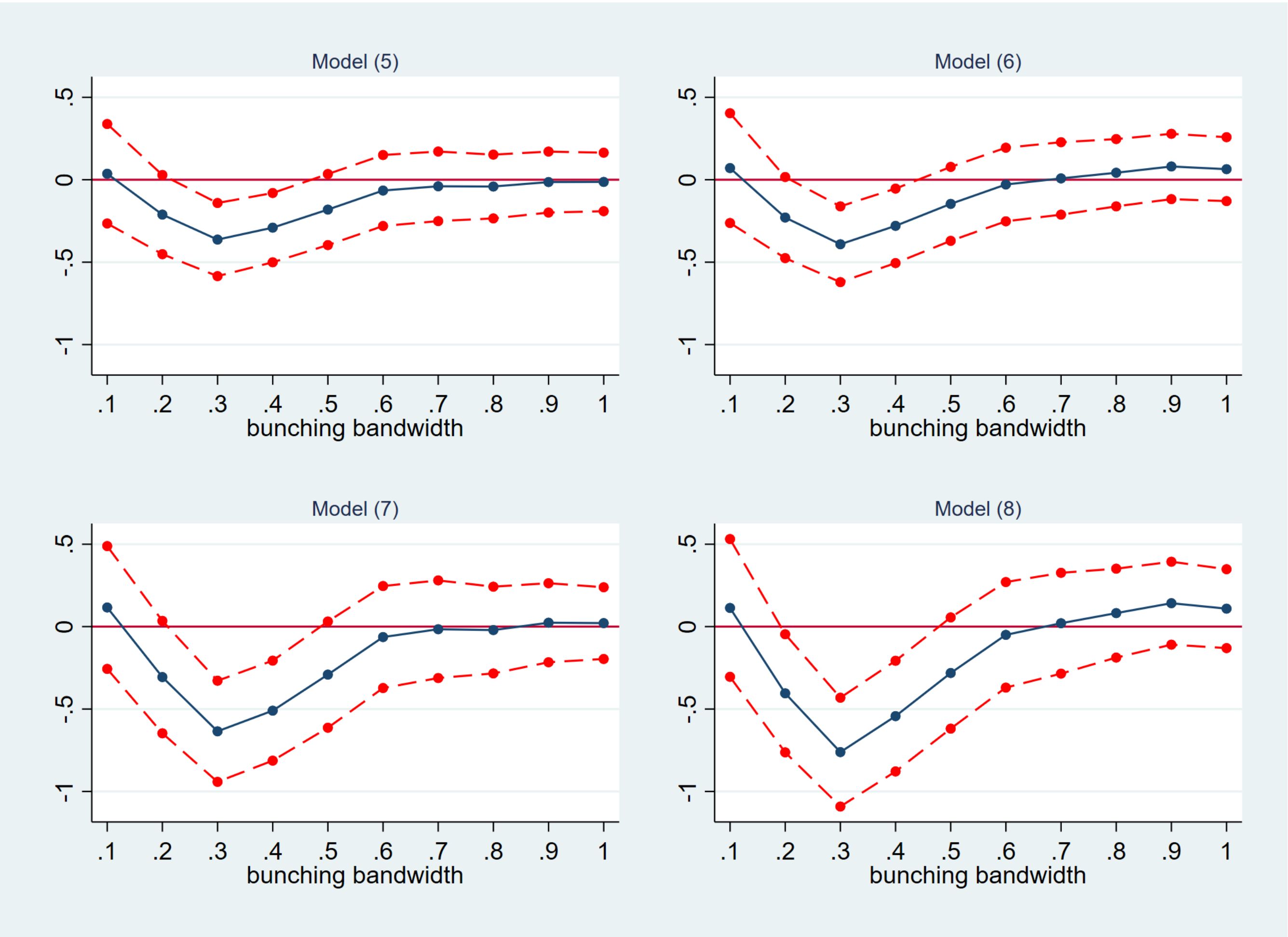
G.2 Overrun costs output (Table 8)



Notes: This table depicts bunching coefficients with their 90% confidence interval obtained when estimating models of columns (5)-(8) of Table 8 using different values for the bandwidth that defines the bunching variable.

Figure 11: Bunching coefficient

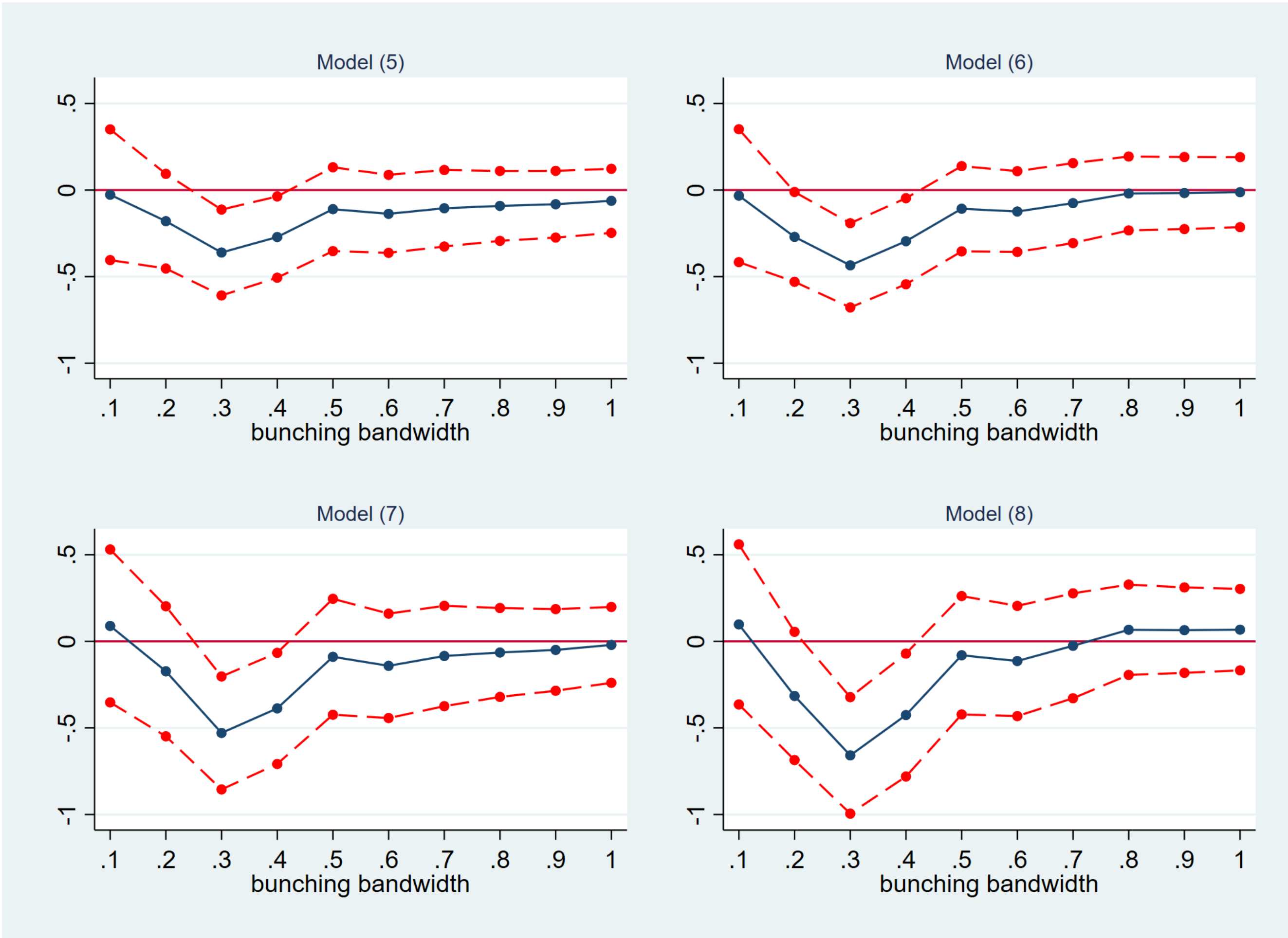
G.3 Completion delay output (Table 9)



Notes: This table depicts bunching coefficients with their 90% confidence interval obtained when estimating models of columns (5)-(8) of Table 9 using different values for the bandwidth that defines the bunching variable.

Figure 12: Bunching coefficients for different values of the bandwidth

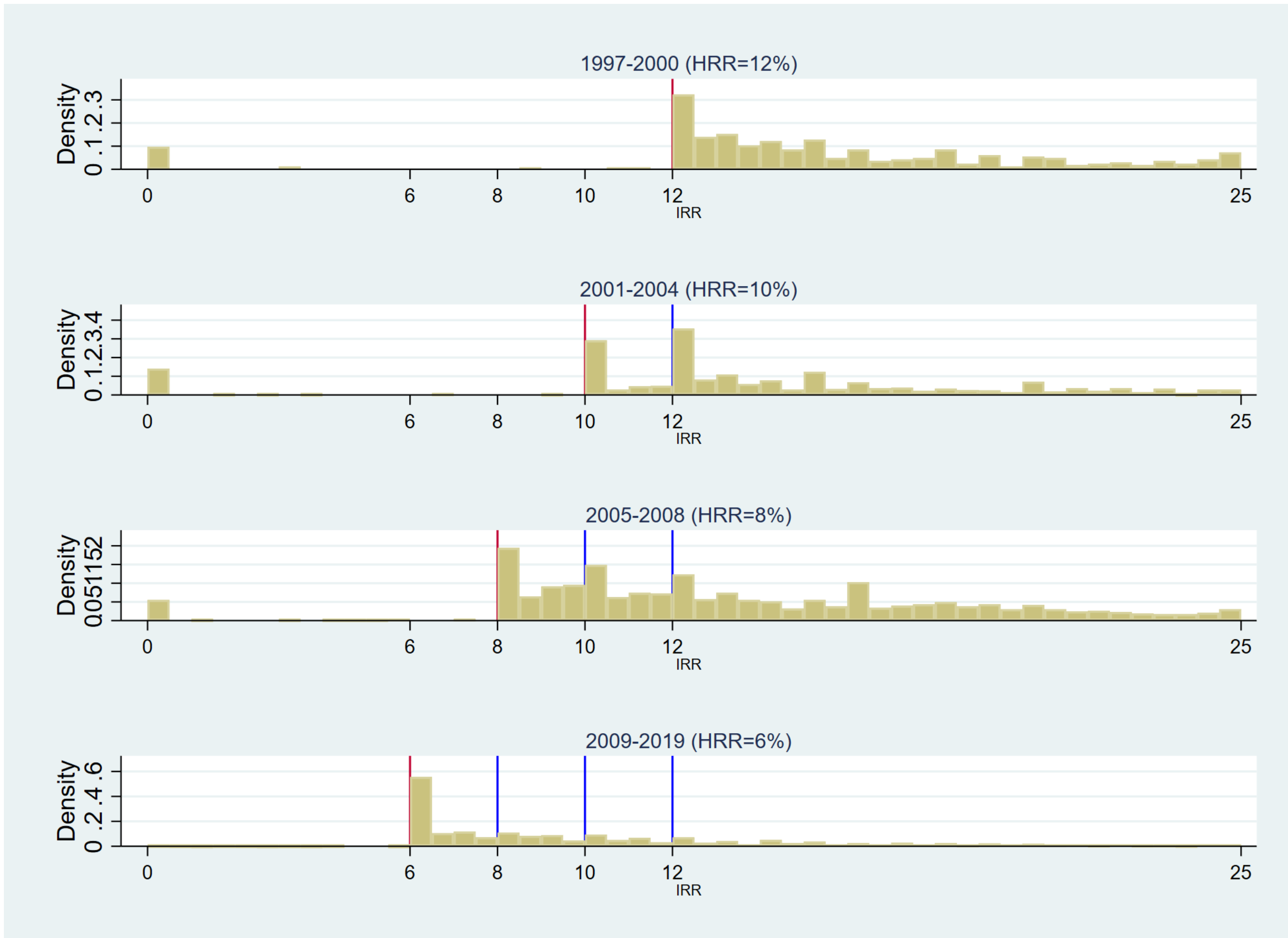
G.4 Completion delay output considering only projects with social-NPV information



Notes: This table depicts bunching coefficients with their 90% confidence interval obtained when estimating models of columns (5)-(8) of Table 9 using different values for the bandwidth that defines the bunching variable.

Figure 13: Bunching coefficients for different values of the bandwidth

H Testing without projects presented on 2020-2021



Notes: This figure replicates Figure 8 without considering projects presented between 2020 and 2021.

Figure 14: ex-ante IRR distribution by HRR-period

Period	$\widehat{b}$	$\widehat{B}$	$\widehat{H}$	$\widehat{B}/\widehat{H}$	y_{lb}	$y_{ub}+0.5$
1997-2000 (HRR=12%)	5.36 (0.75)	0.100	0.105	0.95	9.0	12.5
2001-2004 (HRR=10%)	4.67 (0.88)	0.092	0.09	1.02	7.5	10.5
2005-2008 (HRR=8%)	2.75 (0.42)	0.528	0.537	0.98	6.5	8.5
2009-2019 (HRR=6%)	8.71 (0.66)	0.21	0.21	1.00	1.5	6.5

Notes: This table replicates Table 4 without considering projects presented between 2020 and 2021.

Table 23: Bunching estimators

	Period			
	1997-2000 (HRR=12%)	2001-2004 (HRR=10%)	2005-2008 (HRR=8%)	2009-2019 (HRR=6%)
$\widehat{b}_6$	-	-	-	5.93 (0.27)
	-	-	-	[5.41 , 6.50]
$\widehat{b}_8$	-	-	1.31 (0.13)	0.55 (0.12)
	-	-	[1.08 , 1.55]	[0.31 , 0.83]
$\widehat{b}_{10}$	-	3.19 (0.38)	1.01 (0.12)	0.57 (0.14)
	-	[2.53 , 4.03]	[0.88 , 1.18]	[0.29 , 0.85]
$\widehat{b}_{12}$	2.09 (0.18)	4.97 (0.49)	0.91 (0.14)	0.39 (0.17)
	[1.72 , 2.50]	[4.11 , 6.05]	[0.72 , 1.09]	[0.02 , 0.7]

*Notes:*This table replicates Table 5 without considering projects presented between 2020 and 2021.

Table 24: Bunching estimators using the proposed methodology

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES					*log*(total iterations)					
bunching	0.026	-0.020	0.055	0.026	0.014	0.035	-0.022	0.036	0.078	0.068
	(0.033)	(0.044)	(0.045)	(0.046)	(0.046)	(0.037)	(0.047)	(0.047)	(0.056)	(0.055)
log(social-NPV)			0.030***	0.028***	0.030***			0.025***	0.023***	0.026***
			(0.005)	(0.005)	(0.005)			(0.006)	(0.008)	(0.008)
IRR	-0.000	-0.000	-0.001*	-0.001	-0.002***	0.000	-0.000	-0.000	-0.000	-0.003**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
IRR^2					0.000**					0.000**
					(0.000)					(0.000)
log(n-stages)	1.184***	1.143***	1.128***	1.124***	1.122***	1.163***	1.127***	1.126***	1.116***	1.116***
	(0.042)	(0.045)	(0.044)	(0.047)	(0.047)	(0.045)	(0.048)	(0.048)	(0.063)	(0.063)
Constant	1.653***	1.665***	1.275***	1.299***	1.307***	1.645***	1.652***	1.326***	1.326***	1.323***
	(0.016)	(0.018)	(0.062)	(0.065)	(0.065)	(0.016)	(0.018)	(0.073)	(0.104)	(0.106)
Observations	2,449	2,013	2,013	1,963	1,963	2,311	1,872	1,872	1,398	1,398
R-squared	0.352	0.378	0.394	0.466	0.467	0.456	0.484	0.491	0.629	0.632
Projects	All	NPV	NPV	NPV	NPV	All	NPV	NPV	NPV	NPV
Preparation unit type FE	Yes	Yes	Yes	No	No	No	No	No	No	No
Year FE	Yes	Yes	Yes	No	No	Yes	Yes	Yes	Yes	Yes
Year x Prep Unit type FE	No	No	No	Yes	Yes	No	No	No	No	No
Preparation Unit FE	No	No	No	No	No	Yes	Yes	Yes	No	No
Prep Unit x Year	No	No	No	No	No	No	No	No	Yes	Yes

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: This table replicated Table 6 without considering projects presented between 2020 2021

Table 25: Regressions explaining iterations in approved project

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES					*log*(total iterations)					
log(HRR-distance)	-0.010	-0.013	-0.037***	-0.027***	-0.020	-0.006	-0.009	-0.029***	-0.039***	-0.046***
	(0.007)	(0.008)	(0.009)	(0.009)	(0.014)	(0.008)	(0.009)	(0.010)	(0.013)	(0.018)
log(social-NPV)			0.034***	0.031***	0.031***			0.030***	0.029***	0.029***
			(0.005)	(0.005)	(0.005)			(0.006)	(0.009)	(0.009)
log(HRR-distance)^2					-0.003					0.002
					(0.004)					(0.005)
log(n-stages)	1.179***	1.135***	1.113***	1.112***	1.112***	1.150***	1.120***	1.116***	1.101***	1.103***
	(0.042)	(0.045)	(0.044)	(0.047)	(0.047)	(0.045)	(0.048)	(0.047)	(0.062)	(0.063)
Constant	1.666***	1.680***	1.272***	1.299***	1.303***	1.657***	1.667***	1.310***	1.314***	1.310***
	(0.019)	(0.021)	(0.061)	(0.064)	(0.064)	(0.020)	(0.022)	(0.073)	(0.107)	(0.108)
Observations	2,302	1,992	1,992	1,944	1,944	2,159	1,851	1,851	1,385	1,385
Projects	All	NPV	NPV	NPV	NPV	All	NPV	NPV	NPV	NPV
R-squared	0.364	0.379	0.399	0.469	0.469	0.470	0.486	0.495	0.629	0.629
Preparation unit type FE	Yes	Yes	Yes	No	No	No	No	No	No	No
Year FE	Yes	Yes	Yes	No	No	Yes	Yes	Yes	Yes	Yes
Year x Prep Unit type FE	No	No	No	Yes	Yes	No	No	No	No	No
Preparation Unit FE	No	No	No	No	No	Yes	Yes	Yes	No	No
Prep Unit x Year	No	No	No	No	No	No	No	No	Yes	Yes
elasticity	-0.010	-0.013	-0.036	-0.027	-0.025	-0.00556	-0.009	-0.029	-0.039	-0.040
p-val	0.170	0.113	0.000	0.003	0.009	0.499	0.314	0.001	0.002	0.001

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: This table replicated Table 7 without considering projects presented between 2020 2021

Table 26: Elasticity of average iterations per stage relative to HRR-dsitance in approved projects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES					log(total iterations)					
log(HRR-dist)	-0.015*	-0.015	-0.043***	-0.037***	-0.026*	-0.014	-0.014	-0.046***	-0.048***	-0.042**
	(0.008)	(0.009)	(0.010)	(0.010)	(0.014)	(0.009)	(0.010)	(0.011)	(0.015)	(0.020)
log(social-NPV)			0.041***	0.038***	0.038***			0.045***	0.052***	0.052***
			(0.005)	(0.006)	(0.006)			(0.006)	(0.009)	(0.009)
log(HRR-dist)^2					-0.004					-0.002
					(0.004)					(0.005)
log(n-stages)	1.422***	1.347***	1.312***	1.331***	1.330***	1.397***	1.335***	1.306***	1.298***	1.297***
	(0.045)	(0.048)	(0.047)	(0.051)	(0.051)	(0.049)	(0.052)	(0.051)	(0.068)	(0.068)
Constant	1.330***	1.356***	0.876***	0.903***	0.907***	1.332***	1.355***	0.829***	0.721***	0.725***
	(0.021)	(0.023)	(0.066)	(0.068)	(0.069)	(0.022)	(0.024)	(0.079)	(0.107)	(0.108)
Observations	3,387	2,866	2,866	2,831	2,831	3,228	2,714	2,714	2,101	2,101
R-squared	0.322	0.340	0.358	0.403	0.403	0.410	0.429	0.442	0.562	0.562
Projects	All	NPV	NPV	NPV	NPV	All	NPV	NPV	NPV	NPV
Preparation unit type FE	Yes	Yes	Yes	No	No	No	No	No	No	No
Year FE	Yes	Yes	Yes	No	No	Yes	Yes	Yes	Yes	Yes
Year x Prep Unit type FE	No	No	No	Yes	Yes	No	No	No	No	No
Preparation Unit FE	No	No	No	No	No	Yes	Yes	Yes	No	No
Prep Unit x Year	No	No	No	No	No	No	No	No	Yes	Yes
elasticity	-0.0151	-0.0146	-0.0433	-0.0371	-0.0339	-0.0137	-0.0139	-0.0462	-0.0479	-0.0465
p-val	0.07	0.11	0.00	0.00	0.00	0.13	0.17	0.00	0.00	0.00

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: This table replicated Table 12 without considering projects presented between 2020 2021

Table 27: Average iterations per stage and distance between reported IRR and the hurdle rate.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES				*log*(iterations before RS)				
Ministry	0.120***	0.047	0.002	0.042	0.044	-0.001	0.001	-0.010
	(0.020)	(0.053)	(0.057)	(0.053)	(0.053)	(0.057)	(0.057)	(0.057)
Municipality	0.336***	0.236***	0.220***	0.229***	0.231***	0.213***	0.216***	0.218***
	(0.021)	(0.057)	(0.061)	(0.057)	(0.057)	(0.061)	(0.061)	(0.061)
Other	0.226***	0.095	0.092	0.092	0.092	0.089	0.090	0.102
	(0.031)	(0.104)	(0.112)	(0.104)	(0.104)	(0.112)	(0.112)	(0.112)
$log(HRR\text{-distance})$				-0.008	-0.004	-0.009	-0.000	-0.017***
				(0.005)	(0.008)	(0.006)	(0.009)	(0.006)
$log(HRR\text{-distance})^2$					-0.001		-0.001	
					(0.001)		(0.001)	
log(social-NPV)								0.019***
								(0.004)
Constant	0.769***	0.805***	0.851***	0.825***	0.820***	0.870***	0.862***	0.643***
	(0.019)	(0.051)	(0.055)	(0.053)	(0.053)	(0.057)	(0.057)	(0.070)
Observations	18,975	2,849	2,467	2,849	2,849	2,467	2,467	2,467
R-squared	0.109	0.144	0.169	0.145	0.145	0.170	0.170	0.179
Sample	All	IRR	NPV	IRR	IRR	NPV	NPV	NPV
Municipalidad - Ministerio = 0	0.216	0.190	0.217	0.187	0.187	0.215	0.215	0.228
p-val	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Elasticity				-0.008	-0.005	-0.008	-0.003	-0.016
p-val				0.10	0.45	0.12	0.67	0.003

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: This table replicated Table 13 without considering projects presented between 2020 2021

Table 28: Differences on iterations before approval between different type of organizations

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Attrition							
Ministry	0.093***	0.088***	0.073**	0.096***	0.092***	0.079**	0.074**	0.073**
	(0.013)	(0.034)	(0.037)	(0.034)	(0.034)	(0.037)	(0.037)	(0.037)
Municipality	0.221***	0.179***	0.147***	0.187***	0.181***	0.155***	0.149***	0.150***
	(0.013)	(0.036)	(0.039)	(0.036)	(0.036)	(0.039)	(0.039)	(0.039)
Other	0.153***	0.189***	0.193***	0.192***	0.188***	0.198***	0.195***	0.199***
	(0.019)	(0.068)	(0.074)	(0.067)	(0.067)	(0.073)	(0.073)	(0.073)
log(social-NPV)								0.003
								(0.003)
$log(HRR$-distance)				0.014***	-0.005	0.016***	-0.004	-0.007
				(0.003)	(0.006)	(0.004)	(0.007)	(0.007)
$log(HRR$-distance)^2					0.002***		0.002***	0.002***
					(0.001)		(0.001)	(0.001)
Constant	0.183***	0.109***	0.098***	0.068**	0.096***	0.055	0.084**	0.049
	(0.012)	(0.032)	(0.035)	(0.033)	(0.033)	(0.036)	(0.036)	(0.046)
Observations	21,562	2,912	2,368	2,912	2,912	2,368	2,368	2,368
R-squared	0.441	0.342	0.312	0.347	0.349	0.317	0.320	0.321
Sample	All	IRR	NPV	IRR	IRR	NPV	NPV	NPV
Municipalidad - Ministerio = 0	0.13	0.09	0.07	0.09	0.08	0.07	0.07	0.07
p-val	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: This table replicated Table 14 without considering projects presented between 2020 2021

Table 29: Differences on attrition ratio between different type of organizations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES				*log*(iterations before RS)			
log(budget)	-0.03***		-0.03***	-0.06**	-0.04*	-0.04*	-0.04*
	(0.01)		(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
log(prof)		-0.04**	-0.05***	-0.09**	-0.04	-0.04	-0.04
		(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)
log(social-NPV)						0.01	0.01
						(0.01)	(0.01)
log(HRR-distance)						-0.02	-0.01
						(0.02)	(0.02)
log(HRR-distance)^2							-0.00
							(0.01)
Constant	1.53***	1.23***	1.78***	2.30***	1.93***	1.82***	1.78***
	(0.12)	(0.06)	(0.15)	(0.40)	(0.41)	(0.42)	(0.42)
Observations	7,627	7,666	7,620	730	628	628	628
R-squared	0.13	0.13	0.13	0.18	0.23	0.24	0.24
Sample	All	All	All	IRR	NPV	NPV	NPV
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Scope FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stage FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
elasticity						-0.017	-0.018
p-val						0.29	0.28

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: This table replicated Table 15 without considering projects presented between 2020 2021

Table 30: Differences on iterations before approval between municipalities

VARIABLES	(1)	(2)	(3)	(4) Attrition	(5)	(6)	(7)
log(budget)	-0.00		-0.00	0.01	0.01	0.00	0.00
	(0.00)		(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
log(prof)		-0.01	-0.00	0.04**	0.06***	0.05***	0.05***
		(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
log(social-NPV)						-0.01*	-0.01
						(0.01)	(0.01)
log(HRR-distance)						0.02*	0.02
						(0.01)	(0.01)
$log(\text{HRR-distance})^2$							0.00
							(0.00)
Constant	0.42***	0.43***	0.44***	-0.10	-0.10	0.04	0.03
	(0.06)	(0.03)	(0.08)	(0.22)	(0.24)	(0.25)	(0.24)
Observations	10,738	10,786	10,721	896	718	718	718
R-squared	0.45	0.45	0.45	0.49	0.44	0.44	0.44
Sample	All	All	All	IRR	NPV	NPV	NPV
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Scope FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stage FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: This table replicated Table 16 without considering projects presented between 2020 2021

Table 31: Differences on attrition ratio between municipalities

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