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# The effect of local monitoring on nuclear safety and compliance: Evidence from France[1]

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## Abstract

We estimate the effect of local monitoring and information disclosure on safety and compliance with self-reporting standards in the French nuclear sector. We use a novel dataset on deviations from safety, radiological and environmental standards recorded in the French nuclear fleet since 1978. We find that while local monitoring and information increases significantly compliance, it has little or no direct effect on safety.

## Keywords

Monitoring, compliance, safety regulation, reporting, cuclear safety

## JEL Classification

D22, L51, M42, Q42, Q48, Q58

# 1 Introduction

In this paper, we evaluate the effect of local monitoring and information disclosure activities on safety and compliance in the French nuclear industry. These activities are carried out by so called local information commissions, which are funded by the French departments (i.e. administrative units) that host the nuclear power plants.[1] The main tasks of the local commissions are (i) to monitor safety deviations within the power plant, (ii) to monitor the impact of the plant's operations on the environment and (iii) to communicate any relevant information to the local population. The objective of our paper is to assess the impact of these activities on the extent of evasive reporting in safety self-audits and on the occurrence of deviations from nuclear safety standards (with the latter being a proxy for safety).

In the context of environmental regulation, informational policies such as monitoring and public disclosure of information have been shown to increase the compliance of polluting firms with existing environmental regulations, as well as to decrease their levels of emissions, see Gray and Shimshack (2011) and Shimshack (2014) for comprehensive reviews. While the regulation of nuclear safety shares similarities with the regulations of environmental emissions, it is not clear whether the findings in the environmental literature apply to the nuclear industry. The nuclear industry is characterized by imperfect detection technology, so that an inspection by the regulator might not uncover a major breach of safety rules.[2] In addition, nuclear accidents pose a substantial hazard for the local environment which makes the nuclear industry more publicly visible than the typical polluting industries. This public visibility substantially increases the expected costs for both reporting and nonreporting of safety deviations. As an example, the French nuclear site Fessenheim was invaded by Greenpeace activists in 2014, after it became

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[1] France's administration is organized in several levels below the national government. The French territory is first divided into thirteen administrative regions. Regions are then divided in a total of a hundred departments, which are divided in over thirty-six thousands counties.

[2] Using the vocabulary of the theoretical literature, the audit process is not *error-free*, Evans et al. (2009).

public that its managers had understated the magnitude of an incident that happened earlier that year. Existing theoretical models do not give a clear prediction on the effects of these mixed incentives on the rate of compliance, Evans et al. (2009) and Gilpatric et al. (2011). Finally, unlike in most polluting industries, the agent herself might not detect a deviation from safety standards.

Despite the importance of the nuclear industry as an environmental risk, there are very few statistical studies on the determinants of its safety. A major problem in this context is the scarcity of nuclear accidents. Papers focusing on the technical determinants of safety have therefore either relied on mixed datasets composed of accidents from both nuclear reactors and fuel cycle facilities, (Hirschberg et al., 2004; Sovacool, 2008; Hofert and Wüthrich, 2011; Wheatley et al., 2017), or have used small samples for qualitative analysis, (see e.g. Sovacool, 2008; Hofert and Wüthrich, 2011; Rangel and Lévêque, 2014; Burgherr and Hirshberg, 2014; Wheatley et al., 2017). In the economics literature, there are only three studies - Feinstein (1989), Davis and Wolfram (2012) and Hausman (2014) - that use statistical analysis to evaluate the impact of economic incentives and monitoring on nuclear safety and compliance. A major econometric challenge for the causal evaluation is that economic incentives and monitoring might be set as a reaction to (anticipated) changes in safety and compliance. This reverse causality relationship is a potential source of bias. In addition, changes in the observed levels of safety can be due to changes in both the rate of compliance and the actual level of safety. It is a nontrivial identification task to disentangle these two channels.

We contribute to the literature on nuclear safety and non-compliance in several ways with a particular focus on the three aforementioned problems. First, we use a novel dataset on safety deviations reported in French nuclear power stations. These deviations are considered as important and the nuclear safety authority requires plant managers to report them upon detection. Yet, due to their minor consequences, these events can remain undetected, and managers face countervailing incentives when choosing whether to report detected events. Our dataset contains also information on deviations from radiological and environmental standards, which, although not directly related to nuclear accidents, help draw a richer picture of nuclear safety than previous studies in the economics literature. The main advantage of these three categories - deviations from safety, radiological and environmental standards - is that they are much more numerous than major nuclear accidents. We use the annual budget of the local commissions as a proxy for the monitoring and information disclosure intensity. This proxy variable provides a way to deal with the substantial heterogeneity of activities across local commissions. Moreover, it allows us to quantify the costs associated with the policy. Our dataset spans information between 1978 and 2015 and is rich both in the time and in the cross sectional dimension. To the best our knowledge, this is the first statistical study to use a non-US dataset on nuclear safety, so that the contribution to the external validity of previous studies is particularly important.

Our second contribution is to develop a comprehensive empirical strategy to deal with the endogeneity of monitoring intensity. In our main approach, we utilize a natural experiment triggered by administrative forecasting errors in the annual operating revenues of the French departments. These errors have several attractive features. Once realized, an error may lead to a reassessment of the forecast for future fiscal periods. Since the commissions are financed by their host departments, such a reassessment is likely to induce changes in future budgets of the commissions and thus impact the intensity of local monitoring. Furthermore, fiscal forecasting errors are unanticipated and unrelated to factors determining the safety in the power plants. These errors result from general uncertainty related to tax returns in the French departments. Their rich exogenous variation makes them an attractive instrumental variable for the endogenous budgets of the local commissions. To construct the instrument, we assembled a panel dataset of departmental operational revenues, both realized and forecasted, and matched this dataset to the datasets on local commissions and nuclear safety events. To the best of our knowledge, this is the first paper to use a natural experiment in the context of nuclear safety and compliance.[3] Davis and Wolfram (2012) and Hausman (2014) use time variation in the change of economic incentives and a difference-in-differences approach, while Feinstein (1989) specifies a parametric model of noncompliance, monitoring and safety. Our approach bears similarities with the approaches used in the literature on price and inflation forecasting, see Boneva et al. (2019) for a discussion and further references.

In our second empirical strategy, we exploit exogenous variation of the timing of the treatment. Many of the local commissions were established between 1980 and 1990 as a reaction to three major nuclear accidents (the Three Mile Island accident (1979), the partial meltdown in Saint-Laurent-des-Eaux (1981) and Chernobyl (1986)). Establishing of the commissions in this period was a result of political decisions unrelated to the plant-specific safety factors. Using a difference-in-differences approach, we compare safety levels in monitored plants to safety levels in nonmonitored (or, more precisely, not-yet-monitored) plants. This approach is closely related to the approaches of Davis and Wolfram (2012) and Hausman (2014).

Finally, to disentangle the effect of monitoring on safety from the effect on compliance, we compare the total number of reported events to safety related measures that are very hard or even impossible to manipulate. Those include several reactor reliability measures that react sensitively to changes in the safety level, as well as automatic shutdowns of reactors which are impossible to hide. The former measure is used also by Davis and Wolfram (2012), whereas the latter by both Davis and Wolfram (2012) and Hausman (2014).

Our main empirical finding is that monitoring significantly increases the number of self-reported events. In particular, a €10.000 increase in the annual budget of a commission leads to an increase of 10% in the number of *reported* events. To interpret

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[3] Experiments and natural experiments have rarely been used in the environmental literature on monitoring, self-audits and compliance. Two exceptions are Telle (2013) and Duflo et al. (2013).

our results, we develop a simple model of monitoring, safety and compliance. This model generalizes the standard monitoring models of Evans et al. (2009) and Gilpatric et al. (2011) by allowing for an imperfect endogenous detection ability of the agent. We show that our empirical findings are compatible with a positive effect of monitoring on compliance with safety-related self-reporting standards. This positive effect is in line with the findings of Feinstein (1989), as well as more generally with the results from the environmental enforcement and compliance literature, e.g. Telle (2013) or Duflo et al. (2013). The magnitude of the effect implies that local monitoring is a very cheap economic instrument for enhancing compliance. Furthermore, we find no direct effect of monitoring on safety. This finding contrasts the results in the environmental literature, where information disclosure is found to reduce emissions.

The paper is structured as follows. Section 2 introduces the setup and the data. In section 3, we present our identification strategy. Section 4 presents the results. In section 5, we summarize the predictions of our theoretical model and discuss our empirical findings in the context of these predictions. Section 6 concludes. Supporting results are presented in an appendix.

# 2 Institutional setup and Data

## 2.1 Institutional setup

### Nuclear power and centralized safety regulation in France

The French nuclear fleet is constituted of 58 reactors, located in 19 sites (or plants in the following). It is thus the second largest fleet in the world (after the US one).[4] The fleet is owned by a single utility, Électricité de France (EDF). Roughly 15% of EDF are publicly listed and 85% are owned by the French state.

Nuclear safety is regulated by the Nuclear Safety Authority (ASN) who sets technical

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[4] This holds as of April 2020: https://www.statista.com/statistics/267158/number-of-nuclear-reactors-in-operation-by-country/.

standards regarding the construction, operation and maintenance of all nuclear reactors. In addition, the safety authority establishes reporting criteria which characterize a set of events considered as significant for safety. Upon the detection of an event, the nuclear plant manager has to report it to the safety authority. The objective of this self-reporting mechanism is to promote knowledge spillovers across reactors and to detect generic design weaknesses or organizational failures in order to improve nuclear safety.

To ensure compliance with the self-reporting standards, the nuclear power plants are inspected by ASN inspectors both on a regular and a random basis. If detected, a violation can lead to a prosecution of the firm, displacement of the management and costly temporary shut-downs of the reactors. In addition, anecdotal evidence suggests that failing to declare safety events can have other costly consequences for plant managers such as production losses due to temporary shut-downs or public backlashes.

**Local monitoring** As a reaction to the Three Mile Island accident (1979) and the partial meltdown in Saint-Laurent-des-Eaux (1981), some French departments hosting nuclear stations have organized a form of local monitoring of nuclear power stations through specialized permanent commissions. In 2006, a law made the existence of these local monitoring commissions compulsory in all French Departments hosting nuclear power reactors or fuel cycle facilities.

These local commissions are composed of four groups of members: locally elected officials (mayors from cities neighboring the power station or regional counsellors), members of local environmental associations, members of the nuclear plant workers unions, and competent local citizens. These members are not remunerated for their participation, and some restrictions regarding the composition of the commissions are set by law: elected officials must represent at least 50% of the commission, while each of the other three groups has to constitute at least 10% of the members.

Commissions are funded both by the French Departments and by the Nuclear Safety Authority, with the latter matching the endowments granted by each Department.

There is no regulatory rule regarding the budget amount. As a result, local commissions obtain very heterogeneous budgets, spanning between 5,000 €/year to more than 190,000 €/year.

The activities of the local commissions are also very heterogeneous. First, each commission organizes two to three periodic meetings per year, during which plant managers and the safety authority present the main actions undertaken in the nuclear station. Commission members are provided with a set of documents regarding the operation of the nuclear facility to prepare the meeting, and may ask for specific topics to be addressed. In particular, they receive an account of the occurrences of significant safety events within each reactor of their local station.

Based on these meetings, commissions communicate information to the public. To do so, most commissions invite the press to the periodic meetings, and often make public statements regarding the major decisions made by the plant managers or by the safety authority. Depending on their budgets, commissions may also publish contents on their websites, distribute journals in city halls, mail periodic information letters to citizens in neighboring regions, organize additional open meetings for interested local inhabitants, and even invite citizens from neighboring regions.

Finally, local commissions can hire independent experts in order to carry out assessments of some aspects of the operation of the plant. For instance, past investigations have assessed the environmental impacts of the operation of nuclear stations through radioactivity measurements in local water streams. the results of these investigations are discussed with plant managers and the safety authority.

Further details about the structure and functions of the local commissions can be found in Kerveillant (2018).

**Power plant managers: responsibilities and incentives** The local management of a power plant plays a key role in operational and reporting processes. Although all French nuclear plants are owned by a single firm, many decisions are delegated to the management of each plant. For instance, the reporting of safety events has to be done rapidly after detection and is thus left to the discretion of power plant managers. Furthermore, local management is responsible for taking operational safety measures, training and hiring stuff and making costly investments into new technology. Through these decisions, the local managers are also responsible for the financial performance of the power plant.

The complex business and regulatory environment induces a variety of incentives for these managers. On the operational side, performance-dependent compensation and non-monetary incentives (such as career milestones) provide an incentive for making effort to maintain high operational efficiency and safety. On the regulatory side, reporting a safety event can be costly to the firm and thus indirectly to the management. In particular, the firm can face sanctions when reporting safety events. Regulatory sanctions can consist in additional investments required by the authority.[5] In contrast, failing to report a safety event may lead to a prosecution by the authority or to a public backlash against the local management. As an example, the French station Fessenheim was invaded by Greenpeace activists in 2014, after it became public that its managers had understated the magnitude of an incident that happened earlier that year. One of the main responsible managers was fined and displaced.

The local commissions potentially reinforce the above discussed incentives. On the one hand, a more aggressive information disclosure might be perceived by the management as increased likelihood of a public backlash in the case an event is reported. On the other hand, the presence of environmental inspectors on the site as well as the regular meetings might be perceived as increasing the likelihood that a nonreported event is discovered. Thus, it can be argued the activities of the local monitoring commissions potentially increase the (subjective) expected costs for both reporting and nonreporting of safety events.

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[5] In the environmental literature, these sanctions are usually thought of as a tax on reported emissions.

## 2.2 Data and descriptive statistics

We use a unique dataset which we have assembled from three different sources: ASN, EDF and fourteen local monitoring commissions.

**Outcome variables.** Our main outcome variables are based on recorded deviations from the safety standards of ASN. In the following, these deviations are referred to as (significant) safety events or simply events. ASN classifies each event on the International Nuclear and Radiological Event Scale (levels 0-7). We focus on levels 0-1. Although of much minor severity than nuclear accidents, these events are considered important for the safety of a nuclear reactor. In addition, these events are numerous and thus offer the possibility of a robust statistical analysis (in 2013, for example, there was only one event of severity 2 or higher but several hundred 0/1 events). We obtained information on all (0/1) safety events for the period 1978 - 2015 from the ASN. The data includes information on the exact time and location (i.e. which component of which reactor) of the event, as well as a brief description of the event. From this data, we construct several outcome variables.

The first variable is the total number of safety INES (0/1) events per reactor and year. This level of time aggregation is motivated by the availability of the treatment variable (discussed below). Figure 1 displays a plot of the annual number of these events for the whole fleet. The plot reveals an upward trend, with more than 500 events each year after 2005. One major driver of this trend until shortly after 1997 is the steadily increasing number of reactors (with the youngest reactor being commissioned in 1997). Further potential factors are aging of the reactors as well as the introduction of local monitoring.

The next outcome variable is the annual number of automatic shut-downs (ASD). This is a subset of the safety events. ASD have an impact on the electrical output of the power station and are thus impossible to hide.

Block A of table 1 contains summary statistics for the total number of all safety

Figure 1: The total number of safety events in the French fleet for each year from 1978 to 2015

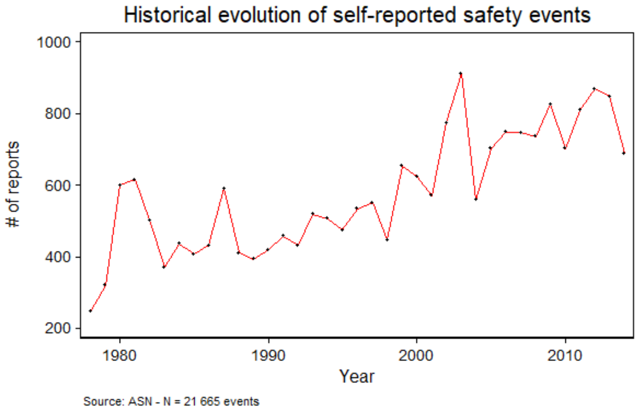

Table 1: Descriptive statistics: reactor-level data.

| | **Variable** | **Mean** | **Std. Dev.** |
|---|---|---|---|
| A | $Safety(ALL)$ | 12.856 | 4.778 |
| | $ASD$ | 0.809 | 0.955 |
| B | Reliability $K_m$ | 0.048 | 0.063 |
| | Reliability $K_f$ | 0.033 | 0.051 |
| C | Environmental | 3.175 | 2.028 |
| | Radiological | 2.813 | 2.053 |

236 observations in 50 reactors from 2007 to 2015 (reactor-year level).

events (Safety (ALL)) and the ASD variables, all measured per reactor and per year. On average, a reactor exhibits roughly 13 events each year and approximately one of them leads to an automatic shut-down of the reactor, although both variables are characterized by substantial variability.

Two further outcome variables are two reliability factors, namely the shares of loss of annual production caused by unanticipated maintenance extensions ($K_m$) and by reactor shutdowns ($K_f$). Unanticipated maintenance extensions and reactor shutdowns are operational disruptions that are closely related to the occurrence of safety relevant events or minor safety considerations. An change in the safety level, therefore, will manifest as a change in those variables.[6] Descriptive statistics for $K_m$ and $K_m$ are shown in Block B of table 1.

The last two outcome variables are two alternative measures of safety. The first one is the number of deviations from environmental standards. These environmental standards have the objective to limit the environmental impact of the operation of the plant (e.g. limits regarding release of radioactive materials outside the station, for instance when rejecting cooling waters into rivers or oceans). The second one is the number of deviations from radiological standards. Radiological standards provide a limit of how much radiation a person can be exposed to in or around the station. Similarly to the safety-related INES 0/1 events, these deviations are subject to self-reporting. Although they are not directly related to nuclear accidents, they help draw a richer picture of nuclear safety. Descriptive statistics of these two variables are displayed in block C of of table 1.

These three categories of variables constitute the most comprehensive characteriza-

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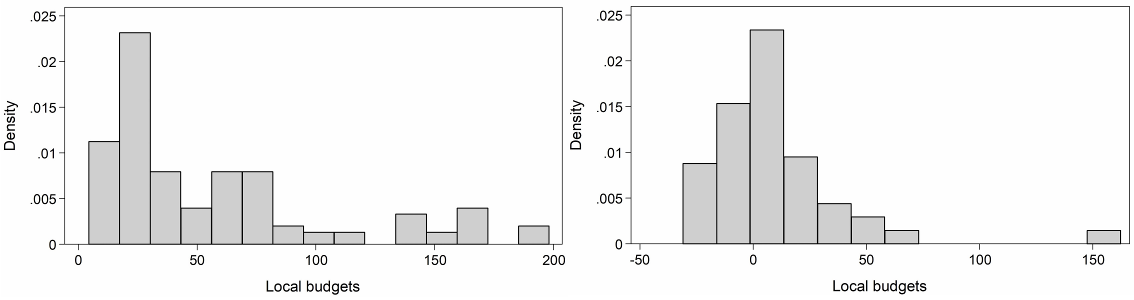
[6] These factors are more closely related to safety than the aggregate reliability factor, which gives the amount of energy produced in a given facility as a share of the total amount of energy that could theoretically be produced in that facility under ideal conditions. The reliability factor is not only influenced by safety, but also by external factors, such as changes in the regulation or yearly inspections, that are not directly linked to the current level of safety. In addition, regular planned maintenance and reactor shutdowns also reduce the reliability factor but they reflect standard operational measures and standards, and not necessarily a change in safety.

tion of a power plant safety used in the economics literature to date. Feinstein (1989) uses the total number of abnormal occurrences, a crude measure of safety that typically includes fewer but more severe safety-related events. ASD is used both by Davis and Wolfram (2012) and Hausman (2014). Hausman (2014) uses four further measures of plant safety that overlap with our variables number of safety events (ALL) and number of radiological events. A variable related to the reliability factors $K_m$ and $K_f$ is used in Davis and Wolfram (2012). The total number of environmental events has no analog in the literature.

**Treatment variable** Our main treatment variable is the annual budget of the local commissions. The data was obtained directly from the commissions. The annual budget can be viewed as a proxy for the intensity of the activities of a local commission. It varies between 4000 €and 198 000 €, with a mean of 52415 €and a standard deviation of 48146 €. Figure 2a presents a histogram of the absolute values of the budget variable,

Figure 2: Annual budgets of local commissions.



(a) Local budgets.

(b) Relative annual change in local budgets.

and figure 2a presents a histogram of the relative changes (in percentage) compared to the previous year (i.e. $\frac{Budget\,t - Budget\,t-1}{Budget\,t-1} \times 100$). The histograms reveal a rich variation, both on a cross-sectional level and over time.

While information on the precise treatment channel is lost, using the budget variable as a treatment has two main advantages. First, there is a substantial heterogeneity in the activities of the local commissions.[7] The budget variable gives a practical way to reduce the dimension of the treatment, while still capturing the intensity of those activities in a meaningful way. Second, this variable makes it straightforward to calculate the total cost of the policy.

For a subsample of the local commissions, we were not able to retrieve information on the budget variable. These commissions and the respective nuclear plants are dropped from the statistical analysis. In section A in the appendix, we present a comparison of characteristics of the retained vs. dropped power plants.

**Controls.** Summary statistics of technical reactor characteristics are displayed in table 2. Reactor age ranges from 8 to 37 with a mean of 28.1 years.[8] The age accounts for potential wearing effects. The variable *size* indicates the number of reactors that a site includes. We also observe the conception type and the nominal capacity. From these two variables (jointly with age) we construct two dummy variables that indicate whether the reactor is first of a site ($FOAS$) or first of a kind ($FOAK$). The $FOAK$ variable indicates whether a reactor is the first built within the groups of reactors sharing a common plant design. $FOAS$ and $FOAK$ reflect possible learning-by-doing effects. Finally, we observe the electricity production of each reactor and the number of days of maintenance. On average, a reactor produced 7 TWh per year and underwent 68 days of annual maintenance.

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[7] We were able to obtain information on these activities for a restricted number of local commissions. In most cases, however, there was little to no time variation of these variables, which leads to a significant loss of identifying variation.

[8] Age is defined here as the time elapsed between the period of observation and the first divergence of the core of the reactor. Other possible definitions of the age of a reactor is the time since the beginning of its construction, its connection to the network, or the start of its commercial operation.

Table 2: Descriptive statistics: control variables.

| **Variable** | | **Mean** | **Std. Dev.** | **Min.** | **Max.** |
|---|---|---|---|---|---|
| Reactor controls | *age* | 28.169 | 5.659 | 8 | 37 |
| | *size* | 3.966 | 1.38 | 2 | 6 |
| | *FOAS* | 0.559 | 0.498 | 0 | 1 |
| | *FOAK* | 0.008 | 0.092 | 0 | 1 |
| | *production* | 6.866 | 1.747 | 2.165 | 11.622 |
| | *maintenance* | 67.568 | 49.839 | 0 | 279 |

236 observations on 50 reactors for the period 2007 - 2015.

# 3 Identification

## 3.1 Two identification problems

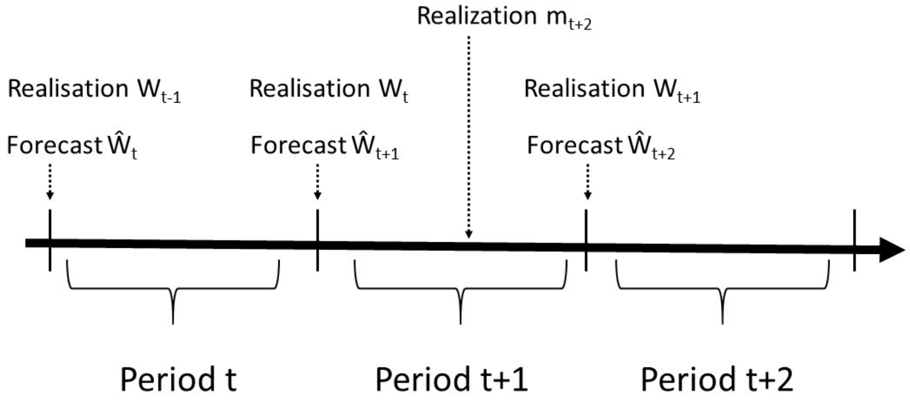
To fix ideas, denote by $E$ the level of safety in a given reactor and by $m$ the intensity of local monitoring and information disclosure. As described in the previous section, we proxy the former by the number of events that ought to be reported to the safety authority and the latter by the budget of the local commission. The reactor manager (the agent) chooses to report a fraction $z$ of the events $E$ to the safety authority (the principal), $z \in [0, 1]$. We are interested in the effect of $m$ on safety $E$ and compliance $z$.

The main problem of identification is that $m$ is potentially endogenous. The level of monitoring and information disclosure might be set in anticipation of changes in safety and compliance, so that $m$ and $E$ (and equivalently, $m$ and $z$) are in a reverse causality relationship.

The second problem of identification is to disentangle the effect of $m$ on $E$ from the effect of $m$ on $z$. In particular, while $m$ and $zE$ are observed to the econometrician, $z$ and $E$ are privite information of the reactor manager. A decrease in the number of events might be due to either improved safety or a decrease in the compliance rate. We refer to this problem as to the channel identification problem.

**Remark.** Additional difficulty arises when the agent does not observe $E$ but a fraction of it. This possibility is addressed in section 5.

Figure 3: Budget Timing

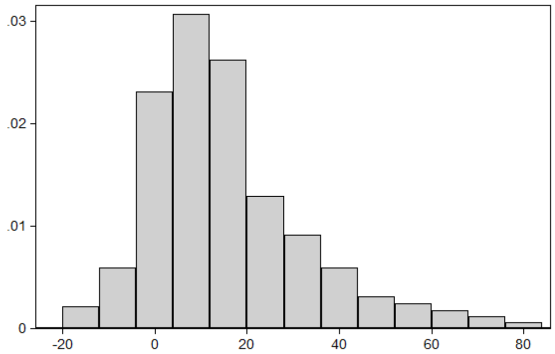


## 3.2 Solution to the endogeneity problem

We deal with the endogeneity of $m$ in two ways: by using an instrumental variable (our main approach) and by using a difference-in-differences approach. We describe the former here and the latter is described directly in the results section. To construct an instrument, we exploit a natural experiment triggered by fiscal forecasting mistakes in the budget of the local government. Consider figure 3. Three fiscal periods (i.e. years) are shown: $t$, $t+1$ and $t+2$. At the beginning of each period, the local departmental government makes a forecast of all departmental revenues and expenditures for the current year. The forecasted net balance (i.e. forecasted revenues - forecasted expenditures) is denoted by $\hat{W}$. $\hat{W}_t$ realizes at the beginning of period $t$ and so on. The actual difference between revenues and expenditures, denoted by $W_t$, realizes at the end of period $t$. Thus, $W_t$ represents the budget of the local government for the subsequent period $t+1$ and the forecast error is $W_t - \hat{W}_t$.

Departments hosting a local commission are required to treat its budget as an op-

Figure 4: Budget Timing



Note: histogram of the annual budget forecast errors (in mio €).

erational expenditure. Denote by $m_t$ the budget of the local commission for the fiscal period $t$. The decision about this budget is taken during the previous period. As an example, the budget $m_{t+2}$ for period $t+2$ is decided upon in period $t+1$, see Figure 3. The forecast error $W_t - \hat{W}_t$ has an impact on how much the department can spend in period $t+1$. It thus potentially affects $m_{t+2}$.

We use the twice lagged departmental forecast error $Z_t := W_{t-2} - \hat{W}_{t-2}$ as an instrument for $m_t$. In the following, we discuss the main properties needed for $Z_t$ to be a valid instrument.

**Variation** A histogram of the empirical distribution of $Z_t$ is shown in figure 4. $Z_t$ has rich variation over its support, which potentially makes it an attractive instrument. Over 80 % of the errors are positive and the distribution is positively skewed. The larger part of its mass lies to the right of 0 which points at conservative budget forecasting. The pattern is similar to the typical patterns found in the public budget forecasting literature, see e.g. Williams and Calabrese (2016).

**Exogeneity** The errors $Z_t$ have an idiosyncratic nature that results from general financial uncertainty on the departmental level. They are almost per definition independent of any factors determining the safety in a nuclear power plant. We provide three arguments in support of that claim. First, the nuclear power plant does not pay taxes to the local government. Its corporate tax is levied on a federal level, which is a historical peculiarity of the French corporate tax system. Second, the power plants play no role as local employers on a government level. As a result of these two arguments, there are no incentives for strategic forecast errors that are related to factors impacting the nuclear safety.[9] Third, we provide indirect evidence in support of the exogeneity assumption. We regress the instrument on observed factors of nuclear safety,

$$Z_t = X_t \beta + \varepsilon. \tag{1}$$

By way of analogy, insignificant estimates $\hat{\beta}$ can be viewed as indirect evidence that $Z_t$ is not related to unobserved factors of safety. This exercise is similar in spirit to the analysis of randomization bias in randomized controlled experiments, see e.g. Duflo et al. (2007). $X$ includes technical features of the reactors such as its age, design and the yearly duration of maintenance. It also includes the dummy variable "Green" which is equal to one whenever the local ruling party is the green party, as well as the size of the local population. The former variable is a proxy for the degree of pro-environmental attitude in the department. Higher degree of pro-environmental attitude of the local population could increase both the costs of reporting and non-reporting of an event. The latter variable is a crude proxy for local GDP. The results are presented in Table 3. The coefficient of the population variable is significant but of economically negligible magnitude. All other coefficients are insignificant.

**Exclusion restriction.** Local governments do not finance the local power plants. Similar to taxes, all financial transfers to the local power plant are determined on a federal level. In addition, the production of the power plant is not restricted to the local market. Thus, there are no direct economic ties between the department and the power plant. Therefore, an adjustment of the government expenditures does not have

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[9] Strategic forecast errors in public budgeting have recently received a lot of interest by the literature, see Williams and Calabrese (2016).

Table 3: Instrument regressed on observed covariates

| **Variable** | INSTR | |
|---|---|---|
| age | -5.767 | (7.785) |
| production | -3.504 | (2.943) |
| maintenance | -0.066 | (0.072) |
| green | -1.509 | (1.077) |
| Pop | 0.000 | (0.000) |
| Intercept | 192.493 | (92.472) |
| Fixed effects | Reactor-Year | |

an effect on the number of reported events other than through the budget of the local commissions.

### 3.3 Solution to the channel identification problem

We solve the channel identification problem by showing that $m$ impacts $zE$ only through $z$. Formally, $\frac{\partial E}{\partial m} = 0$ would imply that $\frac{\partial zE}{\partial m}$ is driven solely by $\frac{\partial z}{\partial m}$. In this case, $\frac{\partial z}{\partial m}$ would be identified provided $\frac{\partial zE}{\partial m}$ is consistently estimated.

We provide two pieces of evidence that $m$ has no impact on $E$. First, we estimate the effect of $m$ on the number of perfectly detectable events ASD. For these events, $z = 1$ and hence $zE = E$, which allows a regression of $E$ on $m$. One caveat with this strategy is that the agent might strategically adapt the level of compliance $z$ on all other events taking into account the number of events that cannot be hidden.

Our second second piece of evidence aims at dealing with this caveat. As discussed in the previous section, the reliability factors have an intimate link to the safety level in a reactor. Changes in safety typically have an effect on $K_m$ and $K_f$. Thus, if local monitoring $m$ has an impact on safety $E$, it is likely to have an (indirect) effect on $K_m$ and $K_f$ as well. Furthermore, $K_m$ and $K_f$ are difficult to manipulate since reliability data is verifiable through production data. Finally, it can be plausibly argued that $K_m$ and $K_f$ are not related to compliance $z$. These two indicators are part of the internal reporting system of EDF and are neither publicly available nor meant to be part of an external report to the regulator. We run a regression of $K_m$ and $K_f$ on $m$ and show that $m$ has no effect. This indirect evidence complements the regression of ASD on $m$.

# 4 Empirical results

## 4.1 OLS and NLS results

We first present regression results obtained with panel OLS and NLS (Poisson regression). The results are displayed in in Table 4. In the first column, the outcome variable is an aggregated reliability factor (defined as $K_f + K_m$). The OLS estimate of the budget effect is positive but insignificant. The second and the third columns contain the results of Poisson regressions with dependent variables the number of ASD events and the number of all safety events, respectively. The estimated effect of the budget variable on ASD is negative and significant at the 5% but is of a vary small magnitude. The

Table 4: OLS and NLS regressions of different measures of safety on the monitoring intensity

| | | 2SLS | |
|---|---|---|---|
| | (1) | (2) | (3) |
| *budget* | 0.000146 | -0.0069** | -0.00096 |
| | (0.000191) | (0.00329) | (0.0018) |
| age | 0.001 | -0.317 | -0.0278 |
| | (0.0047) | (0.286) | (0.096) |
| maintenance | 0.0003*** | 0.0027*** | 0.0016*** |
| | (0.00008) | (0.0008) | (0.0004) |
| Constant | 0.946*** | 6.351 | 3.737** |
| | (0.187) | (4.071) | (1.482) |
| Further controls | Y | Y | Y |
| Observations | 234 | 234 | 234 |
| Year FE | Y | Y | Y |

OLS and NLS regressions of all events per reactor on monitoring intensity and controls. Specifications: (1) OLS regression with Reliability as a dependent variable ; (2) Poisson regression with the number of ASD events as dependent variable; (3) Poisson regression with the number of all events as a dependent variable. *** p<0.01, ** p<0.05, * p<0.1. Robust standard-errors. Reactor-specific fixed effects.

corresponding estimate in the last regression is negative, insignificant and close to 0. The conclusion based on these results would be that the monitoring intensity has no effect on safety and compliance. This interpretation might however be flawed due to potential endogeneity of the budget variable. Nevertheless, as discussed in the next section, we can learn from these estimates about the size and direction of the bias and thus about the underlying data generating mechanism.

## 4.2 Results obtained with an instrumental variable

We now present our main results. For ease of interpretation, we start with results obtained with a panel Two-Stage Least Squares (TSLS) estimation approach with fixed effects (FE). To account for the count nature of some of the outcome variables, we then present additional results using count models.

### 4.2.1 TSLS results

Consider the linear model

$$E_{it} = X_{it}\beta + \beta_{budget} \cdot m_{it} + \eta_i + \delta_t + \varepsilon_{it}, \tag{2}$$

where $E_{it}$ is some safety measure for reactor $i$ at period $t$, $X_{it}$ are control variables, $m_{it}$ is the budget of the local commission that monitors reactor $i$, $\delta_t$ are time dummies, $\eta_i$ are fixed effects and $\varepsilon_{it}$ is an idiosyncratic error term. While $\delta_t$ capture time dependent changes in reporting rules that are common for the whole fleet, the fixed effects account for time-constant unobserved characteristic that are related to safety and to the budget $m$.

**The effect of monitoring on the total number of events.** Consider first the case in which $Y_{it}$ is defined as the total number of reported events in a reactor. Table 5 presents the results of four different TSLS FE regressions that rely on different definitions of the fixed effects $\eta_i$: on a fleet level (i.e. no fixed effects) in specification (1), on capacity level (specification (2)), on site level (specification (3)) and on reactor level (specification (4)). The finer the definition of the fixed effects, the more flexible the model is. The estimated effects $\beta_{budget}$ are positive and significant. The predicted average response to a €10000 increase in the commissions' budgets is an increase of

Table 5: TSLS regressions of the number of all events on the monitoring intensity

| | 2SLS | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *budget* | 0.0651** | 0.0571** | 0.137* | 0.132* |
| | (0.0281) | (0.0244) | (0.0747) | (0.0736) |
| age | -0.626*** | 0.178 | 0.332 | -0.653 |
| | (0.225) | (0.206) | (0.241) | (0.803) |
| production | -0.0253 | -1.137* | -0.758 | -0.942 |
| | (0.390) | (0.603) | (0.616) | (0.731) |
| maintenance | 0.0314*** | 0.0124 | 0.0183 | 0.0135 |
| | (0.00938) | (0.0130) | (0.0121) | (0.0140) |
| size | 0.987 | 1.554** | | |
| | (0.647) | (0.695) | | |
| FOAS | 0.525 | -0.481 | -0.214 | |
| | (0.781) | (0.678) | (0.807) | |
| FOAK | 0.703 | -0.558 | 0.961 | |
| | (1.788) | (1.502) | (2.336) | |
| 1300 MW | 9.191*** | | | |
| | (2.546) | | | |
| 1450 MW | 20.20*** | | | |
| | (4.504) | | | |
| Constant | 1.446 | -12.06 | 13.12 | 32.85 |
| | (8.998) | (9.829) | (8.665) | (24.43) |
| Observations | 234 | 234 | 234 | 234 |
| Year FE | Y | Y | Y | Y |
| Indiv. FE | No | Capacity | Site | Reactor |
| $R^2$ | 0.033 | 0.170 | 0.307 | 0.384 |
| KP rk Wald | 26.59 | 26.83 | 11.82 | 10.3 |
| Wu-Hausman | 15.42 | 13.46 | 6.441 | 6.320 |

TSLS FE regressions of all events per reactor on monitoring intensity and controls. Specifications: (1) No fixed effects; (2) FE on capacity level; (3) FE on site level; (4) FE on reactor level. *** p<0.01, ** p<0.05, * p<0.1. Robust standard-errors.

0.65 to 1.3 *reported* events per reactor and year. This corresponds to an increase of 5% - 10% from the average amount of reported events. Going from specification (1) to specification (4), the estimated coefficient $\beta_{budget}$ tends to increase, with its size in specification (4) being roughly the double of its size in specification (1). This increase is matched by an increase in uncertainty, with the coefficients in specification (3) and (4) being significant at the 10% level, compared to the 5% level for (1) and (2). This is the price paid for the higher flexibility (finer level of the FE) of specifications (3) and (4), and is reflected in a decreased strength of the instrument. The Kleinbergen-Paap statistic of of the First stage of specification (4) is 10.3 and thus slightly larger as the minimum rule-of-thumb size of 10. In comparison, specification (1) has a First-stage F statistic of 26.5, so more than the 2.5 fold larger than the one in specification (1). Table 11 in appendix B.1.1 contains the results of the First-stage regression, which reveal that the estimated effect of the instrument is positive and significant at the 1% level, implying that large positive (negative) forecasting errors lead to a positive (negative) reassessment in the commissions' budgets.

Turning to the controls, the variable *age* has a negative and significant coefficient, which could be due to learning effects. The effect of the *production* variable is negative but insignificant. The length of maintenance has a positive and significant effect on the number of events, which is intuitive since most events occur during maintenance works. The size of the reactor and its properties FOAS and FOAK do not have significant effects. Finally, reactors from the groups of 1450 MW and 1300 MW report more events than those in the 900 MW group, which is consistent with the increase in technical complexity. The estimates of the effect of the control variables in specifications (2)-(4) are predominantly insignificant. The site-level variables 1450 MW and 1300 MW cannot be assessed when site FE (or finer) are included. Analogous restrictions trivially apply for capacity and reactor level variables.

**Channel identification: the effect of monitoring on perfectly detectable**

**events and reliability measures.**

Consider now the case in which $E_{it}$ is defined as either the perfectly detectable ASD events, $K_f$ or $K_m$. The results of the three regression are presented in Table 6.

Table 6: TSLS regressions with outcome variables ASD, $K_m$ and $K_f$

|  | 2SLS<br>(1) | <br>(2) | <br>(3) |
|---|---|---|---|
| *budget* | 0.0046 | -0.000106 | -0.00032 |
| age | -0.0859* | -0.00134 | -0.00122 |
| production | -0.285* | -0.0104* | -0.0158** |
| maintenance | -0.0025 | 0.000289*** | -0.000282** |
| Constant | 0.946*** | 6.351 | 3.737** |
| $R^2$ | 0.076 | 0.46 | 0.091 |
| KP rk Wald | 10.03 | 10.03 | 10.03 |
| Observations | 234 | 234 | 234 |
| Year FE | Y | Y | Y |

TSLS regressions with alternative measures of safety. Specification (1) uses the number of ASD, specification (2) $K_m$ and specification (3) $K_f$ as a measure of safety. *** p<0.01, ** p<0.05, * p<0.1. Robust standard-errors. Reactor-specific fixed effects.

In all 3 regressions, the estimate $\beta_{budget}$ is insignificant and close to 0 in magnitude. Based on the discussion in section 3.3, these results present evidence that monitoring does not impact the safety level of the nuclear reactors. Any effect on the observed number of events must be driven by changes in compliance.

One caveat with this interpretation is the small sample size and the resulting low first-stage F statistic.[10] A more conservative interpretation of the results in table 5 would therefore be that they represent a lower bound for the effect of monitoring on compliance. In section 5, we provide a theoretical foundation for this interpretation.

**The bias of OLS.** A comparison of the TSLS estimates in table 5 with the corresponding OLS estimates in table 4 reveals that the OLS induces a negative bias. This bias is compatible with a negative reverse causal effect of compliance on monitoring. A larger anticipated level of noncompliance (lower $z$) leads to more intensive monitoring,

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[10] The first-stage is identical to the first-stage of specification (4) in table 5.

which in its turn leads to a higher level of compliance through the positive $\beta_{budget}$. As a result, $m$ and the error term $\varepsilon_{it}$ in model (2) are negatively correlated. A formal justification of this intuition is provided in section B.1.2 in the appendix.

### 4.2.2 Results obtained with count models

TSLS is not an optimal method for count data as it might produce negative predicted values. We therefore perform two robustness checks. First, we use a two-stage-residual-inclusion control function approach with a Poisson specification, see Wooldridge (2002, 2015) for a discussion. Second, we use the GMM-IV Poisson estimator discussed in Cameron and Trivedi (2013).

Table 7 contains the results of the Control function approach. Specification (1) uses the number of ASD events as a dependent variable. Specification (2) contains a regression with the total number of events as a dependent variable. As part of the robustness check, we also include several new controls. First, the percentage of votes for the green party at the last election in the department proxies for pro-environmental attitude of the population (denoted by *green*). It is plausible to expect that nuclear plants are exposed to higher social pressure when this share is high, which increases the incentives for both reporting and non-reporting. We also include the variable *load*, which denotes the ratio of energy produced to the hypothetically maximal possible quantity (net of maintenance schedules). Finally, we include the variable *population*, which denotes the size of the population living in the department where the reactor is hosted.

The results are in line with the TSLS results from Table 5. The estimated effect of monitoring is close to zero and insignificant for both the reliability specification (1) and the ASD specification (2). In specifaction (3), the estimate is positive and significant at the 10% level. The first stage reveals that the instrument is highly significant and impacts positively the budget of the local commissions. The additional controls have no significant or economically relevant effects. Omitting them does not change the results

Table 7: Control-function approach estimation with a Poisson specification

| | First-stage | (1) | (2) |
|---|---|---|---|
| Local budget | | -0.00552 | 0.0107* |
| | | (0.0165) | (0.00595) |
| Residuals | | -0.00159 | -0.0128** |
| | | (0.0166) | (0.00547) |
| INSTR | 0.340*** | | |
| | (0.105) | | |
| Age | 5.252*** | -0.308 | 0.0582 |
| | (1.008) | (0.591) | (0.145) |
| Load | -35.40 | -1.271 | 0.102 |
| | (26.63) | (1.807) | (0.673) |
| Maintenance | 0.0114 | 0.00268** | 0.00141*** |
| | (0.0197) | (0.00117) | (0.000471) |
| Population | 89.98 | 7.350 | -2.054 |
| | (79.26) | (11.05) | (3.692) |
| Green Votes | 1.142* | 0.00997 | 0.0000266 |
| | (0.617) | (0.0586) | (0.0199) |
| Constant | -68.17 | 6.091 | 1.587 |
| | (45.49) | (12.53) | (2.343) |
| Observations | 234 | 234 | 234 |
| Adjusted $R^2$ | 0.918 | | |
| F | 294.9 | | |
| r2_p | | 0.147 | 0.140 |

Control-function approach estimations with a Poisson specification. Specification (1) uses the number of ASD, specification (2) the total number of events as a measure of safety. *** p<0.01, ** p<0.05, * p<0.1. Robust standard-errors. Reactor-specific fixed effects.

and so we do not present them here.

The results from the GMM-IV Poisson specification are very similar and are shown in table 12 in appendix B.2.

#### 4.2.3 Results obtained with radiological and environmental events as outcome variables

In this subsection, the outcome variable $E_{it}$ is defined either as the number of environmental events or as the number of radiological events. The results are displayed in table 8. The first two columns contain the TSLS results, the third and the fourth the Control Function approach results, and the last two columns the results with the GMM IV approach. In all approaches, the estimates of $\beta_{budget}$ are positive, and for the environmental events they are also significant. Moreover, the estimates are of similar magnitude as the ones obtained with the number of safety events as a dependent variable. The first-stage results are equivalent to the ones from the previous sections are not shown here.

Table 8: Regressions with environmental and radiological events

| | Environmental<br>TSLS | Radiological<br>TSLS | Environmental<br>Control Function | Radiological<br>Control Function | Environmental<br>GMM IV | Radiological<br>GMM IV |
|---|---|---|---|---|---|---|
| Local budget | 0.0490* | 0.0262 | 0.0164* | 0.00927 | 0.0181** | 0.00848 |
| | (0.0250) | (0.0225) | (0.00976) | (0.00855) | (0.00865) | (0.00703) |
| Residuals | | | -0.00814 | -0.0152 | | |
| | | | (0.0103) | (0.00929) | | |
| Age | -0.381 | 0.127 | -0.107 | 0.0605 | -0.105 | 0.0224 |
| | (0.409) | (0.537) | (0.158) | (0.228) | (0.131) | (0.154) |
| Load | 3.380 | 0.916 | 1.186 | -0.145 | 1.319 | -0.0876 |
| | (2.441) | (2.323) | (1.168) | (1.182) | (0.992) | (1.001) |
| Maintenance | 0.00149 | 0.00770*** | 0.000332 | 0.00255** | 0.000270 | 0.00246*** |
| | (0.00165) | (0.00206) | (0.000831) | (0.00109) | (0.000608) | (0.000707) |
| Population | 2.166 | 11.67 | 0.775 | 3.166 | 0.934 | 4.260 |
| | (9.972) | (15.06) | (4.029) | (6.466) | (3.381) | (4.504) |
| Green Votes | 0.164** | -0.0274 | 0.0566* | -0.00508 | 0.0553* | -0.00949 |
| | (0.0718) | (0.0821) | (0.0343) | (0.0301) | (0.0286) | (0.0280) |
| Constant | 3.125 | -7.027 | -1.432 | -2.244 | -1.705 | -1.781 |
| | (7.701) | (7.827) | (7.035) | (6.564) | (2.637) | (2.353) |
| Observations | 234 | 234 | 234 | 234 | 234 | |
| Adjusted $R^2$ | 0.242 | 0.167 | | | | |
| First-stage F stat | 10.42 | 10.42 | | | | |

Regressions with two alternative measures of safety: number of environmental events and number of radiological events. *** p<0.01, ** p<0.05, * p<0.1. Robust standard-errors. Reactor-specific fixed effects.

### 4.3 Results based on a difference-in-differences approach

In this section, we specify the following model:

$$E_{it} = \beta_0 + \beta_{LC} D_{it} + \delta_t + \eta_i + \varepsilon_{it}, \tag{3}$$

with $E_{it}$ being the total count of safety events, $D_{it}$ a binary variable indicating whether for reactor $i$ there was a local commission established in or before period $t$, $\delta_t$ is a year dummy, $\eta_i$ is a reactor fixed effect and $\varepsilon_{it}$ is an idiosyncratic noise term. The model thus compares the treated reactors (i.e. monitored by a commission) with the not (yet) treated reactors.

This specification can be motivated in the following way. First, the majority of local commissions were established between 1980 and 1990 as a reaction to three nuclear accidents: the Three Mile Island accident (1979), the partial meltdown in Saint-Laurent-des-Eaux (1981) and Chernobyl (1986). The process of establishing, and in particular the time order, was motivated by political reasons and did not reflect differences in safety level within the French fleet, Kerveillant (2018) and Schneider (2008). As an example, the correlation between the year of divergence of a nuclear plant and the year of establishing a local commission is -0.12, which implies a very low correlation between the age of a plant and the time to establishing a commission, see table 13 in the appendix. Therefore, the timing of establishing a commission (and hence the variable $D_{it}$) can be assumed exogenous. In our baseline estimation, we restrict the period of observation to 1978 - 1992, i.e. to two years before and after the period 1980-1990. To assess the sensitivity of the results with respect to this choice, we vary the upper bound to 1988 and 1990.

The results are displayed in table 9. The first column contains the result of the period 1978 - 1988, the second column of the period 1978-1990 and the third of the period 1978-1992 (the baseline period). In all three specifications, the effect of establishing a

Table 9: Evolution of reporting during creation of local commissions

| | Safety - ALL (OLS; 78-88) | Safety - ALL (OLS; 78-90) | Safety - ALL (OLS; 78-92) |
|---|---|---|---|
| exist_CLI | $5.144^{*}$ | $5.171^{***}$ | $4.122^{**}$ |
| | (2.756) | (1.908) | (1.711) |
| Reactor Fixed-effects | Y | Y | Y |
| Year Fixed-effects | Y | Y | Y |
| Observations | 255 | 351 | 454 |
| Adjusted $R^2$ | 0.472 | 0.455 | 0.460 |
| Regression model | OLS | OLS | OLS |

Standard errors in parentheses

$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

For all stations, exist_CLI = 0 prior to the creation of the local commission, 1 afterwards.

commission $\beta_{LC}$ is positive and significant. The lowest estimate is equal to 4.122. To put this estimate into a perspective, note that the total number of events for the whole fleet in the period 1978 and 1990 varies between roughly 400 and 600 per year. An increase of 4.122 events per reactor corresponds therefore to an increase between 10% and 20% for the whole fleet in the respective period of observation.

In appendix B.3.2, we use this framework to assess possible learning effects over time.

**Remark.** We are not able to repeat the analysis in this section using the radiological and environmental events as we only observe these since 1996.

# 5 Microeconomic interpretation of the empirical results

Our empirical findings are that increased monitoring and information disclosure have (i) a positive and significant effect on the number of reported effects and an (ii) insignificant effect on the number of perfectly detectable events. We bear in mind that (ii) might be due to a small sample. There are two channels through which $m$ can impact $z$. On the one hand, a more aggressive information disclosure might be perceived by the agent as increased likelihood of a public backlash in the case an event is reported. On the other hand, the presence of environmental inspectors on the site, as well as the reviews of performance and safety by the members of the local information commission increase the probability that a nonreported event is discovered by the principal. Thus, higher $m$ increases the (subjective) expected costs for both reporting and nonreporting of safety events.

To simplify the discussion, we refer to the cost related to a reported event as "a penalty" (we denote it by $\alpha$) and to the cost incurred when a nonreported event is uncovered by the regulator as "a sanction" ($\psi$). On the one hand, microeconomic theory predicts that increasing either penalties or sanctions has a nonnegative effect on safety,

$$\partial E/\partial \alpha \leq 0 \qquad \text{and} \qquad \partial E/\partial \psi \leq 0, \tag{4}$$

see for example Evans et al. (2009) and Gilpatric et al. (2011). On the other hand, these models predict opposite effects for penalties and sanctions on compliance:

$$\partial z/\partial \alpha \leq 0 \qquad \text{and} \qquad \partial z/\partial \psi \geq 0. \tag{5}$$

The interpretation of our results in light of those theoretical predictions is that compliance and information disclosure in the French fleet have a positive impact on compliance. Our estimates can be interpreted as a lower bound, since the effect on safety must be unambiguously nonnegative. In particular, if our nonsignificant finding is a small sample failure to detect a decrease in perfectly detectable events, then the estimated coefficients represent a mixture of a large positive coefficient for compliance and a small negative coefficient for safety. Furthermore, the increase in compliance implies that the perceived costs for nonreporting an event (the sanctions component) plays a larger role than the perceived penalty for reporting.

**Imperfect detection by the agent.** So far, we have implicitly assumed that the agent has a perfect knowledge of the safety level and therefore knows $E$. This is also the assumption of the theoretical literature. In the appendix, we develop a model, in which the agent detects an event with a probability $\rho \in (0, 1)$. This assumption is plausible for the context of the nuclear industry due to the high complexity. Here we briefly summarize the predictions of that model. We consider two cases. In the first one, the detection ability $\rho$ is exogenously given. We can state the following lemma:

**Lemma 5.1.** *If* $0 < \rho < 1$ *is exogenously given, then relationships* (4) *and* (5) *continue to hold.*

The intuition for this result is that a positive exogenous constant does not change the first order conditions of the agent. The lemma 5.1 corresponds to proposition C.1 in the appendix, where we also present the proof.

Consider now the case in which it is costly for the agent to detect events. The detection costs reflects the effort level (e.g. the number of hired workers) that is chosen by the agent. We can state the following lemma (see section C.3 in the appendix):

**Lemma 5.2.** *Assume that the cost incurred by the agent is convex in the exerted effort, then relationshipts* (4) *and* (5) *continue to hold with* $z$ *replaced by* $\rho$*. Moreover, it holds* $z = 1$ *(perfect compliance).*

The intuition behind this result is that when detection ($\rho$) is costly for the agent, it makes no sense to choose $z < 1$. In particular, for any value $z < 1$, the agent can increase her objective function by making a lower effort. The reason for this is that it is never optimal to make an effort to detect events that are later not reported to the principal. Thus, when detection is costly, the effort chosen to detect an event plays the role of the level of compliance $z$ when $\rho$ is either equal to 1 or exogenously given. The interpretation of our results remains therefore unchanged.

# 6 Conclusion

In this paper, we presented empirical evidence that local monitoring and information disclosure increase the number of self-reported safety events in the French nuclear fleet.

Our results indicate that local monitoring is a powerful and cheap instrument to enhance compliance with self-reporting standards. In contrast, we found no effect on short-term safety levels. One line of future research would be to study the treatment heterogeneity. Understanding which monitoring and information disclosure activities drive the effect is a key to designing effective policies.

# A Attrition bias, local monitoring and reporting behaviours

Table 10 presents a comparison of means of observable variables in the sample used for estimations and the sample of excluded observations, for which we could not obtain data regarding the budget of the local commission. The comparison reveals significant differences in several variables which implies that the external validity of the study might be violated. The interpretation of the results has therefore to be restricted only on the retained sample.

Table 10: Descriptive statistics: attrition bias.

| **Variable** | **Sample mean** | **Out-of-sample mean** | **t-statistic** | **p-value** |
|---|---|---|---|---|
| ALL | 12.85 | 13.67 | 1.81 | 0.07 |
| ASD | 0.87 | 0.89 | 0.23 | 0.82 |
| $K_m$ | 0.04 | 0.05 | 1.25 | 0.21 |
| $K_f$ | 0.03 | 0.04 | 2.24 | 0.03 |
| Age | 29 | 24 | 9.49 | 0.00 |
| Production | 6.86 | 7.28 | 2.50 | 0.01 |
| Maintenance | 66.98 | 68.59 | 0.34 | 0.73 |

Note: In this table, we compare the mean value of some observables for the pairs of reactor-year within our panel (sample means), with the pairs of reactor-year for which we did not obtain data regarding the budgets of local commissions (out-of-sample mean).

# B Additional results and tables

## B.1 Results and tables corresponding to section 4.2.1 in the main text

### B.1.1 First stage results

Table 11: First-stage results of 2SLS regressions in Table 5 in the main text

| | (1) | (2) |
|---|---|---|
| INSTR | 0.298*** | 0.772*** |
| age | 3.332*** | 5.230*** |
| production | -3.798* | -2.566 |
| maintenance | -0.0647 | -0.0659 |
| size | | -27.41*** |
| FOAS | | -7.981 |
| FOAK | | 45.36*** |
| 1300.Power_Group | | -41.85*** |
| 1450.Power_Group | | -55.97* |
| Constant | | 275.9*** |
| Observations | 234 | 234 |
| Fixed effects | R-Y | Y |

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors. Specification (1) assumes reactor-level FE and corresponds to the first stage of specification 4 in Table 5. Specification (2) assumes no fixed effects and corresponds to specification (1) in Table 5.

### B.1.2 Bias of OLS estimates

Formally, consider the simultaneous equations

$$z = \beta_{budget} m + \epsilon_z \tag{6}$$

$$m = \alpha z + \epsilon_m . \tag{7}$$

Assume for simplicity that $z$ and $m$ have no other confounders, so that $cov\{\epsilon_z, \epsilon_m\} = 0$. Denote the variance of $\epsilon_z$ by $\sigma^2_{\epsilon_z}$. It follows that

$$\begin{aligned} &cov\{m, \epsilon_z\} = cov\{\alpha z + \epsilon_m, \epsilon_z\} = \alpha cov\{z, \epsilon_z\} \\ &= \alpha(\beta_{budget} cov\{m, \epsilon_z\} + \sigma^2_{\epsilon}), \end{aligned}$$

which when solved for $cov\{m, \epsilon_z\}$ yields

$$cov\{m, \epsilon_z\} = \frac{\alpha \sigma^2_{\epsilon}}{1 - \alpha \beta_{budget}}. \tag{8}$$

A negative correlation $cov\{m, \epsilon_z\}$ implies thus $\alpha < 0$ provided $|\alpha \beta_{budget}| < 0$. This conclusion remains valid if in equation (7) $z$ is replaced by the anticipated (by the local commission) $\tilde{z}$, provided $z$ and $\tilde{z}$ are positively correlated. Hence, the negative OLS bias suggests that an increase in anticipated noncompliance leads to increased intensity of monitoring.

## B.2 Results obtained with GMM and a poisson specification

Table 12 contains results obtained with GMM Poisson IV estimation approach.

Table 12: GMM IV estimation with a Poisson specification

| | (1) | (2) |
|---|---|---|
| Local budgets | -0.00519 | 0.0121** |
| | (0.0143) | (0.00604) |
| Age -0.310 | 0.0608 | |
| | (0.301) | (0.115) |
| Population | 7.445 | -1.956 |
| | (7.854) | (2.948) |
| Green Votes | 0.0100 | 0.000667 |
| | (0.0429) | (0.0174) |
| Load | -1.254 | 0.141 |
| | (1.133) | (0.492) |
| Maintenance | 0.00270*** | 0.00144*** |
| | (0.000795) | (0.000452) |
| Constant | 6.070 | 1.409 |
| | (4.898) | (1.982) |
| Observations | 234 | 234 |

GMM Poisson IV specification. Specification (1) uses the number of ASD, specification (2) the total number of events as a measure of safety. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Robust standard-errors. Reactor-specific fixed effects.

## B.3 Tables and further results corresponding to the difference-in-differences approach

### B.3.1 Tables

Table 13 enlists the year of divergence for each nuclear site as well as the year of establishing a local commission in the corresponding department.

Table 13: Year of divergence vs. year of establishing a local commission

| Site | Divergence | Local Commission |
|---|---|---|
| Belleville | 1988 | 1983 |
| Blayais | 1982 | 1993 |
| Bugey | 1979 | 1992 |
| Cattenom | 1989 | 1983 |
| Chinon B | 1985 | 1993 |
| Chooz B | 1997 | 1982 |
| Civaux | 1998 | 1981 |
| Cruas | 1984 | 1984 |
| Dampierre | 1981 | 2006 |
| Fessenheim | 1977 | 1977 |
| Flamanville | 1986 | 1993 |
| Golfech | 1992 | 1982 |
| Gravelines | 1982 | 1987 |
| Nogent | 1988 | 1993 |
| Paluel | 1985 | 1999 |
| Penly | 1991 | 1999 |
| Saint-Alban | 1986 | 2006 |
| Saint-Laurent B | 1981 | 1980 |
| Tricastin | 1980 | 1983 |

### B.3.2 Learning effects

To assess possible learning effects over time in this framework, we modify model (3) in two steps.[11] In a first step, we estimate the model

$$Y_{ijt} = \beta_j + v_t + \varepsilon_{ijt}, \tag{9}$$

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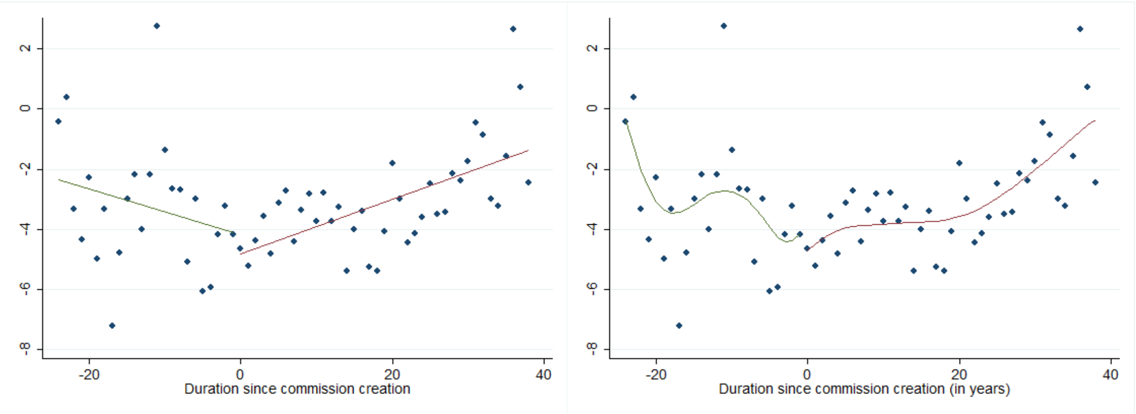
[11] We borrow this idea from Hausman (2014).

where $Y_{ijt}$ is the number of reported events in reactor $i$, calendar year $t$ and $j$ years after introduction of local commission, $v_t$ is a year-fixed-effect, and $\varepsilon_{ijt}$ is the idiosyncratic error term. Negative $j$ are interpreted as the number of periods prior introduction of a commission. This specification produces an year-after-implementation average $\hat{\beta}_j$, which could be interpreted as the learning effect of the commission. In a second step, we run two regressions - one for values $j < 0$ and one for values $j \geq 0$. These two regressions capture different patterns before and after monitoring has started. Figure 5a presents a fit produced with a linear model, while 5b presents a fit with a nonparametric polynomial (lowess) model. The dots in the plot represent the estimates $\beta_j$. In both cases, the fit produced with coefficients $\beta_j$ with $j \geq 0$ is increasing, while the fit with $j < 0$ is decreasing.

Figure 5: Annual budgets of local commissions.



(a) Linear regression.

(b) Lowess.

# C A model of monitoring and compliance

This section presents a principal-agent model which describes the effect of monitoring on the levels of safety care and transparency exerted by a monitored agent. In particular, we show that monitoring provides countervailing incentives to report significant safety events: although more monitoring always leads to more safety care, it can also, in some instances, lead to less transparency. The model is adapted from Evans et al. (2009) and Gilpatric et al. (2011), and introduces a novel discussion of the identification issue that arises when a monitored agent subject to a reporting mechanism can select both his ability to detect deviations and his compliance level (i.e. his propensity to report detected deviations).

Contrarily to the existing theoretical literature on audit mechanisms[12], we do not model explicitly the optimization problem of the regulator, and only model the best-response of an agent to the exogenous audit mechanism set by the principal. The determination of the optimal audit mechanism is irrelevant in our context, as our empirical estimation consists in using exogenous variations in monitoring intensity to characterize the response of plant managers.

## C.1 The model

Suppose that an agent (the manager) operates a nuclear power reactor subject to a reporting mechanism requiring the agent to report the occurrences of deviations or safety events to the principal, who enforces the reporting mechanism using random inspections. Formally, let $s$ represent the amount of safety effort (or safety care) exerted by the plant manager. $s$ is assumed to be a positive real number. Let $E_{tot}(s)$ be a continuous variable capturing the total number of events that occur during a year in a nuclear power reactor.[13] Intuitively, we assume that $E_{tot}(s = 0) = E_0 > 0$: under no safety

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[12] See for instance e.g. Macho-Stadler and Pérez-Castrillo (2006); Evans et al. (2009); Gilpatric et al. (2011), and Zahran et al. (2014).

[13] For tractability of the model, we ignore the count nature of these events.

care, there is a striclty positive number of safety events occurring in the power station. Next, we assume that $E_{tot}$ decreases when $s$ increases and that $lim_{s \to +\infty} E_{tot}(s) = 0$. In other words, increasing safety care reduces the number of occurrences of safety events, but curbing this number down to 0 requires an infinite amount of care.

As safety care is costly, but provides private benefits such as increased reliability of the power station or better reputation for the manager, we assume there is a cost function $C(s)$ convex with $C(0) = 0$, $C'(0) < 0$, $C'' > 0$, and $lim_{s \to +\infty} C(s) = +\infty$. The positive initial derivative of the cost function $C$ captures the private benefits of safety care. Under these assumptions, and in the absence of any safety regulation, the agent would choose the privately optimal level of care $s^{priv}$, satisfying $C'(s^{priv}) = 0$, and associated with a given number of events $E^{priv} = E_{tot}(s^{priv})$.[14]

Second, when $E_{tot}(s)$ events occur, we assume that the manager only detects a fraction $\rho \in [0; 1]$ of these events. After detecting these events, the agent chooses to report a fraction $z$ of observed events to the principal. Here, one can consider that detection failures can either be due to the limited attention of plant workers, or to organizational failures. We assume that the agent cannot report an event which he did not really observe, hence $z \in [0; 1]$. In other words, the agent observes $E_{obs} = \rho E_{tot}$ and reports the quantity $zE_{obs} = z\rho E_{tot}$ to the principal.

In addition, the principal conducts with probability $q$ a random inspection of the agent's facility, during which inspectors try to uncover events that may not have been reported by the agent. As inspectors have limited time to perform their inspections, we assume that audits do not perfectly reveal all unreported events. More specifically, let $u$ be a random variable distributed according to a cumulative distribution $F$ and density $f$ over $[0; 1]$. The value taken by $u$ represents the fraction of $E_{tot}$ detected by the principal during audits. When $u$ takes values greater than $z\rho$, the audit reveals a number of events larger than what the agent reported. When $u$ takes values greater than

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[14] Otherwise, in the absence of regulation the agent would choose $s = +\infty$.

$\rho$, the audit reveals events that were not observed by the manager. Hence, the quantity $Q$ of events revealed by the audit is:

$$Q(u) = \begin{cases} 0 & \text{if } u < z\rho \\ (u - z\rho)E_{tot} & \text{if } u \geq z\rho \end{cases} \tag{10}$$

and the expected quantity of events revealed by the audit is $\mathbb{E}Q = E_{tot} \int_{z\rho}^{1} (u - z\rho) f(u) du$.

After the inspection, the authority inflicts a unit penalty $\alpha$ for each event reported, and a sanction $q\beta$ for each event that was not reported but discovered during the inspection. Using previous notations, the penalty associated with reporting $z\rho E_{tot}$ events is $\alpha z\rho E_{tot}$. Likewise, the sanction faced by the agent when some events are not reported is $q\beta \mathbb{E}Q = q\beta E_{tot} \int_{z\rho}^{1} (u - z\rho) f(u) du$.

Penalties $\alpha$ embody the direct consequences of reporting, such as the administrative costs incurred by the manager when reporting, or such as mandatory investments required by the safety authority due to the new information derived from the knowledge accumulated thanks to the reported events. Regarding sanctions, the probability of inspection $q$ can be thought of as the frequency of planned or unplanned inspections. The sanction $\beta$ embodies the consequences of non-declaration, such as legal prosecution, public backlashes or increases in the stringency of the regulatory oversight.

Hence, under this reporting mechanism with imperfect audits and imperfect observation of events, a risk-neutral agent maximizes the following quantity:

$$\max_{s,z,\rho} -C(s) - \mu(\rho, z)E_{tot}(s) \tag{11}$$

where $\mu(\rho, z)$ is the unit cost of safety events faced by the agent: $\mu(z) = \alpha z\rho + q\beta \int_{z\rho}^{1} (u - z\rho) f(u) du$. This model is a generaliyation of Evans et al. (2009) and Gilpatric et al. (2011). The main novelty of our model is that the imprecision of the audit describes both the fact that the agent may fail to detect safety events, and the fact that the principal has only limited audit resources.

## C.2 Best response of the agent when detection ability is exogenous

Suppose first that detection ability $\rho$ is exogenous. The agent is left with the discretion of choosing safety care $s$ and the level of compliance $z$. Let $z^\star$ and $s^\star$ be the best response played by the agent given an exogenous audit mechanism characterized by penalty $\alpha$ and sanctions $q\beta$. We note this audit mechanism $(\alpha; q\beta)$.

Provided $\alpha < q\beta$ and detection abilities are *large enough*,[15] the existence of an interior solution for $z^\star$ is ensured. This condition captures the idea that if the penalty for reporting is higher than the sanction for non-reporting, then the agent never reports and an interior $z^\star$ cannot exist.

Likewise, if the cost function $C(s)$ is *convex enough*,[16] then there exist an interior $s^\star$ that maximizes equation (11). Otherwise, the incentives provided by the monitoring scheme are sufficient to ensure that the agent exerts a level of safety care associated with no occurrences of safety events. This assumption captures the idea that reducing the number of safety events to 0 is infinitely costly, so that there always exist an interior solution for the optimal level of safety care, which results in a strictly positive number of safety events.

We can then derive the following comparative statics properties of a change in the monitoring scheme $(\alpha; q\beta)$ on compliance $z^\star$, on the amount of events occurring $E_{tot}(s^\star)$, and on the total observed quantity of reports $z^\star \rho E_{tot}(s^\star)$, which we note $z^\star E^\star$ for simplicity.

**Proposition C.1.** *At an interior solution, the following results hold:*

- $\frac{\partial s^\star}{\partial \alpha} > 0$*: a marginal increase in penalties leads to an increase in safety care,*

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[15] Specifically, the first order condition that defines an interior $z^\star$ is $z^\star = \frac{1}{\rho} F^{-1}(1 - \frac{\alpha}{q\beta})$. Hence, a necessary condition for the existence of an interior solution for $z^\star$ is $\rho > F^{-1}(1 - \frac{\alpha}{q\beta})$.

[16] A sufficient condition is $lim_{s \to +\infty} C'(s) = +\infty$.

- $\frac{\partial z^\star}{\partial \alpha} < 0$: *a marginal increase in penalties leads to a decrease in compliance,*

- $\frac{\partial s^\star}{\partial q\beta} > 0$: *a marginal increase in sanctions leads to an increase in safety care,*

- $\frac{\partial z^\star}{\partial q\beta} > 0$: *a marginal increase in sanctions leads to an increase in compliance.*

**Proof 1.** *Let* $\mu(z) = \alpha\rho z + q\beta\int_{z\rho}^{1}(u - z\rho)f(u)du$. *From equation* (11), *one can derive the following first-order condition characterizing the existence of an interior solution for the agent's choice:*

$$z^\star = \frac{1}{\rho}F^{-1}(1 - \frac{\alpha}{q\beta}) \tag{12}$$

$$B'(E^\star_{tot}) = \mu(z^\star) \tag{13}$$

*The effect of a change in* $\alpha$ *or* $q\beta$ *on* $z^\star$ *derives directly from equation* (12). *Then, using the envelope theorem in equation* (13), *we can differentiate* $\mu(z^\star)$ *with respect to either* $\alpha$ *or* $q\beta$, *which yields the second part of the result.*

This result is identical to the result derived by Evans et al. (2009) and Gilpatric et al. (2011). The intuition why the result remains unchanged is that $\rho$ is simply treated as a positive constant and thus does not change the First Order Condition of the agent.

**Corollary 1.** *A marginal change in the level of penalties* $\alpha$ *has an unambiguous effect on the total quantity of reports* $z^\star E^\star$.

**Proof 2.** *This is a direct consequence of the first two comparative statics in proposition C.1. An increase in penalties first increases safety care and thus reduces the total number of occurrences of safety events. Second, the increase in penalties leads to a decrease in compliance. Overall, the increase in penalties leads to a decrease in the quantity of events reported to the principal.*

**Corollary 2.** *A marginal change in* $q\beta$ *has an ambiguous effect on* $z^\star E^\star$.

**Proof 3.** *To see this, we can write:*

$$\frac{\partial z^\star E^\star}{\partial q\beta} = E_{tot}(s^\star)\frac{\partial z^\star}{\partial q\beta} + z^\star \frac{\partial E_{tot}}{\partial s}(s^\star)\frac{\partial s^\star}{\partial q\beta} \tag{14}$$

*Proposition C.1 ensures that the first term in the right-hand side of* (14) *is positive, while the second term is negative. The variation in observed reports induced by a marginal change in $q\beta$ is determined by the relative size of these two terms, and in particular by the relative amplitude of the variations in compliance and in safety care.*

## C.3 Best response of the agent under costly detection ability

We now relax the assumption that detection abilities $\rho$ are exogenous. The agent can now choose how much effort to dedicate to $\rho$, at cost $e(\rho)$. We assume that exerting detection efforts is costly, and that this cost is convex, so as to find interior solutions.

In this new setting, the optimization problem boils down to:

$$\max_{s,z,\rho} -C(s) - \mu(\rho, z)E_{tot}(s) - e(\rho) \tag{15}$$

The solution to this multidimensional choice problem can be derived intuitively. First, notice that when $\rho$ is costly it makes no sense to choose $z \neq 1$. Indeed, if $z < 1$ then the agent can improve his objective by reducing the value of $\rho$. As effort is costly, it is never optimal to incur a cost to detect events which are in turn not reported. Then, the best response of the agent to the monitoring scheme $(\alpha; q\beta)$ is identical to the solution described in proposition C.1, after replacing $z$ by $\rho$.

This extension of the model first shows that when detection of violations are costly, there are no incentives for a reporting agent to fail to comply with reporting guidelines. Instead, it is the effort exerted by the agent to identify non-compliant situations that ought to be monitored by the regulator, to ensure that all relevant events are well identified by the agent.

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