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Coping practices and the spatial dimension of authority design

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Abstract

Frontline implementers develop coping practices to deal with implementation burdens. Unfortunately, we have only limited knowledge of how widespread and systematic these practices are applied. This paper provides a comprehensive analysis of the enforcement activities carried out in the context of the European Union Industrial Emission Directive, relying on a quantitative data set that summarizes the information from more than 2000 inspection reports published by the German state Baden-Württemberg. Our analysis reveals that inspectors tend to give priority to sites that (1) are closer and easier to reach and (2) that pose only a small risk to their environment. These findings indicate that implementers are primarily guided by concerns over the quantitative rather than the qualitative aspects of their work. These insights highlight that public authorities' spatial location is a crucial, yet still unexplored factor in the study of policy implementation.

Evidence for practice

- Frontline implementers develop coping practices to deal with implementation burdens.
- It is important to understand what drives implementers in their decision to prioritize parts of the target group or the execution of some implementation tasks over others.
- We find that environmental inspectors tend to prioritize industrial plants that are close to the location of their authority and those that only pose a small risk to their environment.
- In particular, the first aspect reveals that it makes a crucial difference *where* exactly an implementing authority is ultimately located.
- In consequence, we provide a novel approach to how the spatial location of public authorities can be improved.

INTRODUCTION

Frontline implementers make sure that policies are complied with and thus can be considered the most influential actors in shaping policy outcomes. They operate in various areas such as social, environmental, and education policy. As typical street-level bureaucrats (SLBs), implementers must often perform their tasks with limited resources and ever-growing expectations raised by central decision-makers (Lipsky, 2010; Wightman et al., 2022). Consequently, they must develop adequate coping strategies that allow them to "master, tolerate, or reduce external and internal demands and conflicts among them" (Folkman & Lazarus, 1989, p. 223) to achieve a manageable workload. This can involve implementers focus on executing some implementation tasks or controlling some selected parts of the target group (Winter & Nielsen, 2008).

While previous scholarly contributions have made substantial progress in identifying, classifying, and examining different coping strategies (Tummers et al., 2015), we have limited knowledge of how widespread and systematic these coping strategies are applied in practice.

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Are there systematic, large-scale differences in whom and how implementers prioritize when facing resource constraints? And if so, do implementers try to minimize the time and expenses associated with their work to maximize their impact, or to find a balance between these options?

To address these questions, the paper provides a comprehensive analysis of the enforcement activities carried out in the context of the European Union (EU) Industrial Emission Directive (IED). Our analysis relies on a quantitative data set that summarizes the central information of more than 2000 inspection reports carried out by the responsible public authorities in the German state of Baden-Württemberg. We find that environmental inspectors in Baden-Württemberg make (indeed) strong use of coping practices. More precisely, our empirical analysis reveals that implementers systematically 'cream' for efficiency. Inspectors check industrial plants more frequently the closer they are to the authority's location. In addition, the analysis reveals that inspectors give priority to plants that pose a small hazard to their environment.

With these findings, we contribute to the public administration literature in different ways. First, we test the theoretical argument on coping patterns empirically in a large-scale quantitative analysis. This way, we move beyond the qualitative single-case-study approach typical to the study of coping practices. Second, we provide novel insights that the spatial location of implementation authorities is a decisive, yet unexplored, factor in the implementation process.

The remainder of this article is structured as follows: We begin with a short overview of the literature on frontline implementers and coping practices and discuss the remaining shortcomings in this research strand (Section 2). In the next step, we hypothesize how implementers can use their discretion to deal with their work burden and how the corresponding behavioral patterns can be linked to different types of coping practices (Section 3). In the following Section 4, we introduce our empirical case and discuss the measurement of our dependent and independent variables. Thereafter, we turn to the statistical analysis and discuss our empirical observations in light of the theoretical expectations (Section 5). In the discussion section, we illustrate how the knowledge gained in the previous sections can help to optimize the spatial location and thus the design of public authorities (Section 6). Finally, Section 7 concludes.

LITERATURE REVIEW: FRONTLINE IMPLEMENTERS AND COPING PRACTICES

Lipsky's seminal piece on "street-level bureaucracy" popularized the concept of street-level bureaucracy" (Lipsky, 2010). In essence, Lipsky posits that "policy implementation in the end comes down to the people who actually implement it" (p. 8). These frontline implementers must often deal with and operate in a high-stress environment caused by scarce resources and high demand. At the same time, they possess great discretionary freedom and autonomy in their daily work (Brodkin, 2007, 2011). Against this background, frontline implementers develop elaborated coping mechanisms that allow them to handle their large case- and workloads.

These coping strategies have different effects upon both the implementers' everyday life and the citizens' encounter with the state (Maynard-Moody & Musheno, 2012; Thomann et al., 2018; Tummers et al., 2015). In the end, however, *all* coping mechanisms have the potential to entail significant consequences for the proper functioning and acceptance of the respective policies in question and, in the aggregate, for the democratic system at large (Adam et al., 2019). Differential treatment, goal displacement, insufficient consideration, or even complete negligence of parts of the target population can all result from the above-discussed coping practices.

While the implementers' coping strategies, as well as their causes and consequences, are thus widely acknowledged and discussed in the literature, different research gaps still prevail. In particular, we have only limited knowledge on (1) how widespread and—even more importantly—how systematic these coping practices are applied in practice; and (2) if implementers rely on some decision heuristics more than on others. These blind spots are primarily due to the fact that most scholarly contributions on SLBs and coping practices are single case studies based on qualitative data gathered via personal interviews (Tummers et al., 2015). While this is generally a valid research strategy given the subject matter, a quantitative research approach might allow us to understand the overall prevalence of coping strategies and the resulting implementation deficits (Van Engen, 2019).

Moreover, it seems promising to move beyond the use of self-reported data that are typically gathered in interviews and survey questionnaires. This type of individual-level data is helpful, if not indispensable, to better understand the dynamics that shape frontline implementation. Yet, it also suffers from well-known problems such as social desirability.

In this paper, we address these issues in two ways. First, we provide a large-scale quantitative analysis of the coping practices of frontline implementers. Second, we base our analysis on the key information extracted from environmental inspection records.

THEORETICAL DISCUSSION: ENVIRONMENTAL INSPECTORS AND COPING PRACTICES

This study investigates a specific type of frontline implementers, namely environmental inspectors. The inspectors' job entails several aspects that make it both similar and different to classic SLBs in the 'Lipskian' sense. On the one hand, just as most SLBs, inspectors are relatively

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'low-level' public service that must handle a very high workload with only limited personnel, financial, and time resources (Li, 2023; Maor & Sulitzeanu-Kenan, 2013; May & Wood, 2003). Moreover, an inspector's job has the classic features of SLBs as it includes direct and intense interactions between public representatives and their 'clients' (Sevä & Jagers, 2013). This adds up to "several thousand kilometers on the road, hundreds of handshakes, countless orders, injunctions, recommendations and agreements, as well as an extremely large number of meetings and telephone conversations" (Nielsen, 2015, p. 867). These interactions, however, are difficult to control and thus leave great discretion to the inspectors on how to behave before, during, and after these inspections. On the other hand, some characteristics make the work of regulators different from the street-level bureaucracies engaged in service delivery typically studied using an SLB perspective. Most importantly, inspectors do not have to face social and psychological pressure from the target group given that businesses (as opposed to welfare benefits recipients) typically do *not* ask for 'help' and instead prefer to be left alone by the inspectors.[1] In the context of this paper, we primarily focus and build our argument on the first two features, that is, the fact that inspectors must perform (1) multiple tasks with limited resources but (2) relatively large discretion in their daily work.

But how can environmental inspectors use their 'discretion' to cope with their work burden? There are multiple ways how inspectors can react to handle their high cases and workload. In the context of this paper, we focus on "creaming" (Lipsky, 2010) as a potential coping strategy. In the case of creaming, practitioners prioritize some clients, cases, or tasks to the disadvantage of others. The arguments developed in the following rest on the assumption that the inspectors *try* to do a good job, even when facing quite adverse circumstances and conditions. This assumption is perfectly in line with the existing SLB research. For Lipsky, SLBs are not 'bad' or 'lazy' people. Instead, they are changed and shaped by their daily experience (Lipsky, 2010, p. 85). In response to these experiences, SLBs either drop out of public service or, if they remain, develop practices to "reduce the stress and strain of their work in such a way that allows them to reduce the discord between their ideals (…) and the nature of their day-to-day practice" (Evans, 2015, p. 239). In other words, implementers are expected to adjust to reality but *not* to give up their initial motivation for the job entirely.

Winter and Nielsen (2008) essentially propose two subtypes of creaming; or "rationing output" as they call it (see also Vedung, 2015).[2] First, frontline implementers can cream for *quantitative improvement*.[3] This implies that implementers try to" to carry out many outputs per unit of time, while ignoring the outcomes" (Vedung, 2015, p. 17). Given a fixed resource budget, implementers can only increase their 'output per unit of time' by doing more at the same time, that is, by minimizing the time and effort they spend on each case and task. Quantitative improvement thus typically implies improved *efficiency*. Second, frontline implementers can go for *effectiveness and qualitative improvements* (Winter & Nielsen, 2008). Here, frontline implementers focus on those cases for which their actions exert the strongest impact and thus exhibit the highest potential for achieving substantive policy goals.

But what are the observable patterns of behavior that follow from the different coping strategies? In essence, we can expect that applying one or some of these coping practices should result in differential treatment of the industrial sites up for inspection. To count as a coping strategy or practice, these differential treatments should not only occasionally occur, for instance, for a single implementer or working day but *systematically* across a wide range of different inspections.

There are numerous ways how inspectors can save time on each inspection. Yet, one of the most time-consuming and, at the same time, most unproductive activities is the travel to the industrial plant. Thus, inspectors *creaming for efficiency* will prioritize industrial plants closer to their authority's locations that are easier to reach and access. This should result in accurate and on-time visits in case of closer inspection sites and in the opposite scenario for more distant ones. The overall prevalence of this coping strategy can be summarized with the following hypothesis:

> **Hypothesis H1.** Inspectors prioritize plants closer to the inspectors' authority over more distant ones.

For inspectors that strive for *qualitative improvements*, by contrast, we can expect quite different behavioral patterns. Here, implementers should choose to visit those industrial plants that are at high risk of causing substantial damage. This risk can depend on various aspects such as the dangerousness of the substances used or the vulnerability of a plant's environment. The extent to which inspectors *cream for effectiveness* can thus be captured by the following hypothesis:

> **Hypothesis H2.** Inspectors prioritize plants with a higher risk potential over less risky ones.

RESEARCH DESIGN

To test our theoretical propositions, we provide a comprehensive analysis of the enforcement activities carried out in the context of the EU IED (Directive 2010/75/EU). The IED entered into force in 2011 and implied a substantial increase in implementation burden for the national inspectors.[4] The IED pursues an integrated approach towards industrial emissions covering the industrial emissions to air, water, and land, and heavily relies on the use

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of so-called 'best available techniques' (BAT). Put simply, BAT reference documents list all relevant activities in a specific industrial sector as well as the most appropriate and best-performing technologies in the respective context. Given these documents, industrial plants are required always to apply and install the most updated technologies. If the inspectors find that a given industrial plant does not comply with the provision set by the IED and is not able to fix the issue, "the operation of the installation (…) or relevant part thereof shall be suspended" (Directive 2010/75/EU).

In the context of IED, we focus on the enforcement activities carried out by the implementation authorities in the German state of Baden-Württemberg from 2013 to 2020. Baden-Württemberg is among the wealthiest states in Germany and since 2011 led by a green government that has put a strong emphasis on environmental concerns (Hörisch & Wurster, 2019). Moreover, German public administration is underpinned by a strong legalistic tradition that stresses strict adherence to rules and processes (Bach et al., 2017). In combination, these aspects make the occurrence of pronounced coping strategies and resulting implementation deficits in the case of Baden-Württemberg—from a theoretical point of view—a rather unlikely scenario and thus interesting to examine.

The fact that the government of Baden-Württemberg is very committed to environmental protection is also reflected in the fact that the state's implementation authorities report very transparently on their enforcement activities. While the IED requires *all* EU member states to report on their inspections, we find substantial variation across both countries and subnational entities in the type, amount, and comprehensiveness of the information provided. In contrast to other EU countries and German states, for instance, Baden-Württemberg also reports on the risk rank of the installations checked. As discussed in more detail below, this information is crucial to calculate the inspections' legal due date and, based on this information, possible implementation delays and deficits.

The state of Baden-Württemberg is separated into four governmental districts ('Regierungsbezirke'). These governmental districts are Freiburg, Karlsruhe, Stuttgart and Tübingen. The governmental district administrations ('Regierungspräsidien') are located in the four eponymous cities. All four administrations are staffed by and under the direct control and supervision of the state's government.

Dependent variable

We rely on the data provided by the government of Baden-Württemberg (Landesanstalt für Umwelt Baden-Würrtemberg, 2020). To infer the deviation from the legal due date of an inspection, we first calculate the *interval* of inspections for a time point (t) for each industrial plant (i). We can infer the interval based on the date of the reported inspection. Assuming that each visit is also noted correctly in the database, we calculate it by counting the days between subsequent visits which can be formalized as follows:

$$Interval_{it} = Inspection_{it} - Inspection_{it-1}$$

This reduces the viable observations to plants that were at least inspected twice with the first inspection being removed from the sample. To guarantee the comparability between the observations, we only included plants where *all* inspections were routine inspections. Furthermore, we exclude plants with at least one inspection interval below 180 days. If inspectors find a violation during their inspection, in some cases the plant operators have the chance to alleviate the problem within 180 days. Removing these observations guarantees that the measured intervals are comparable and representative of the typical inspection routines and are not caused by other factors like violations reported to the agency or follow-ups after prior infringements.[5]

Based on the reported *risk rank*, we can then measure the *Deviation* from the required inspection's legal due date at a time point (t) for each industrial plant (i). The *risk rank* directly indicates how long the inspection interval of a given industrial plant should be. It ranges from '1' to '3'—'1' indicating an inspection interval of one year, '2' of two years, and '3' of three years. Therefore, the $Deviation_{i,t}$ can be defined as follows:

$$Deviation_{it} = Interval_{it} - (Risk\ Rank_{it} * 365)$$

We multiply the *risk rank* by 365 since we measure the interval in days. While the resulting variable $Deviation_{it}$ is our main dependent variable, we also estimate all models with the $Interval_{it}$ as our key dependent variable as the transformation of the variable might change the results retrieved.

Independent variables

To operationalize the distance to the industrial plant, we leverage the fact that the state's inspection reports indicate the addresses of all plants visited. Since we are interested in the additional burden caused by longer distances, we measure the distance in *hours driven* between the address of the industrial plant and the address of the responsible agency. This operationalization accounts for the fact that the simple travel or route distance (indicated in kilometers) is not always indicative of the real burden imposed on the inspector. For example, 100 km on the German highway might go by faster than 80 km on curvy country roads and, consequently, might be perceived as a lesser burden by the inspectors. To estimate the travel time, we used the *Distance Matrix API*[6] by Google assuming that the main means of transport of an

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inspector is driving by car. The API relies on the data also found in Google Maps to return an estimation of the time-driven between two points. The estimate of the time-driven accounts for the expected traffic. To get a common frame of reference, we set the departure time at 10 am on a Monday.

Before calculating the distances, we geocoded all addresses, therefore, transformed them into longitude and latitude coordinates, using the *Geocoding API*[7] also by Google. Geocoding the locations in advance guarantees that the API correctly identified the addresses. The resulting coordinates were manually inspected and checked for correctness.

Lastly, to assess the risk posed by an industrial plant, we used the classification provided by the respective authority (Government of Baden-Württemberg, 2013a). Here, the risk rank of an industrial plant is determined by taking into account the substances used, the sensitivity of the local surrounding, and the potential consequences of accidents arising from the installation. Following the classification, we construct a categorical variable differentiating three levels of risk—high (risk rank = 1), medium (risk rank = 2), and low (risk rank = 3). As described before, a *higher* risk level automatically stipulates more frequent inspections. In the models, we always use low-risk as the baseline category.

Control variables

We added several control variables to the analysis. Administrative circulars indicate that in some cases inspectors must include local agencies in the inspection process (Government of Baden-Württemberg, 2021). The higher level of coordination needed could influence the length of the inspection interval when it comes to inspections. Therefore, we added a binary control variable that captures if other *agencies* were involved in the process.

Furthermore, we added a binary variable indicating if an external (private) *agent* was involved in the inspection process. Plant operators can commission state-certified experts that administer the authorization and supervision procedure on their behalf. These experts collect all necessary information and then make an appointment for inspections. As argued by the literature on "regulatory intermediaries" (Abbott et al., 2017) and "hybrid regimes" (Havinga & Verbruggen, 2017), this procedure can be expected to overall ease the process and thus to lead to timelier on-spot visits.

We also tested control variables for the different industry sectors. While most sectors did *not* cause any significant variance, industrial plants connected to the production of cars and electronic components and plants processing wood consistently affected the observed delay. Therefore, we included individual dummies for each of those plant types.

We also control for the possibility that implementers react to changes in their workload. To account for this, we construct a variable that captures the implementation pressure in each quarter of the year for a given district. We calculate this variable by summing up the number of industrial sites that should be and have not been already controlled in each quarter based on the previous control dates. For this, we rely on the same data as for the calculation of our dependent variable. Additionally, we also control for residual temporal effects (see below).

Moreover, it might be the case that inspectors do engage in *multiple* inspections on the same day within a given area. To account for this, we capture the possibility of multiple inspections by a binary variable that becomes one for a given industrial site when (1) on the same day (2) another plant in a 10, 20, 30, or 40 km radius got visited.

Lastly, we account for spatial and temporal effects. Given that our data is time series data we account for temporal variation by including yearly fixed effects and by quarter district-level random intercepts for some models. To capture spatial variation, we estimate spatial autoregressive models that include a spatially lagged dependent variable to account for unobserved local aspects. While these models should capture variation that is caused by the location of sites, we also estimate a set of linear mixed-effect models where we account directly for the nested structure by including random intercepts on the quarter district level.

EMPIRICAL ANALYSIS

The dataset includes 2298 inspections of 801 industrial plants that met the criteria outlined before. Given that we can only identify implementation deficits for sites that were already inspected at least once, the final data set for our analysis includes 1497 observations (2298 total observations–801 first visits). The 801 industrial plants are distributed spatially in 595 unique locations. Thus, some plants share the same location, for example, when they are situated in the same industrial park or represent different plants of the same company.

Descriptive data

Figure 1 shows how our dependent variable, as well as the two main independent variables, are distributed both spatially and numerically. Looking at the numerical distribution of the independent variable we can see that it has a pronounced peak around zero, which is also the median of the distribution. Therefore, we observe that in most instances the inspection is close to the intended interval. Still, we observe a plethora of instances where the inspection interval deviates from the norm, that is, the legal due date. Positive deviations can be interpreted as implementation delays, while negative values can be interpreted as (too) early fulfilments. Figure 1a reveals that inspectors

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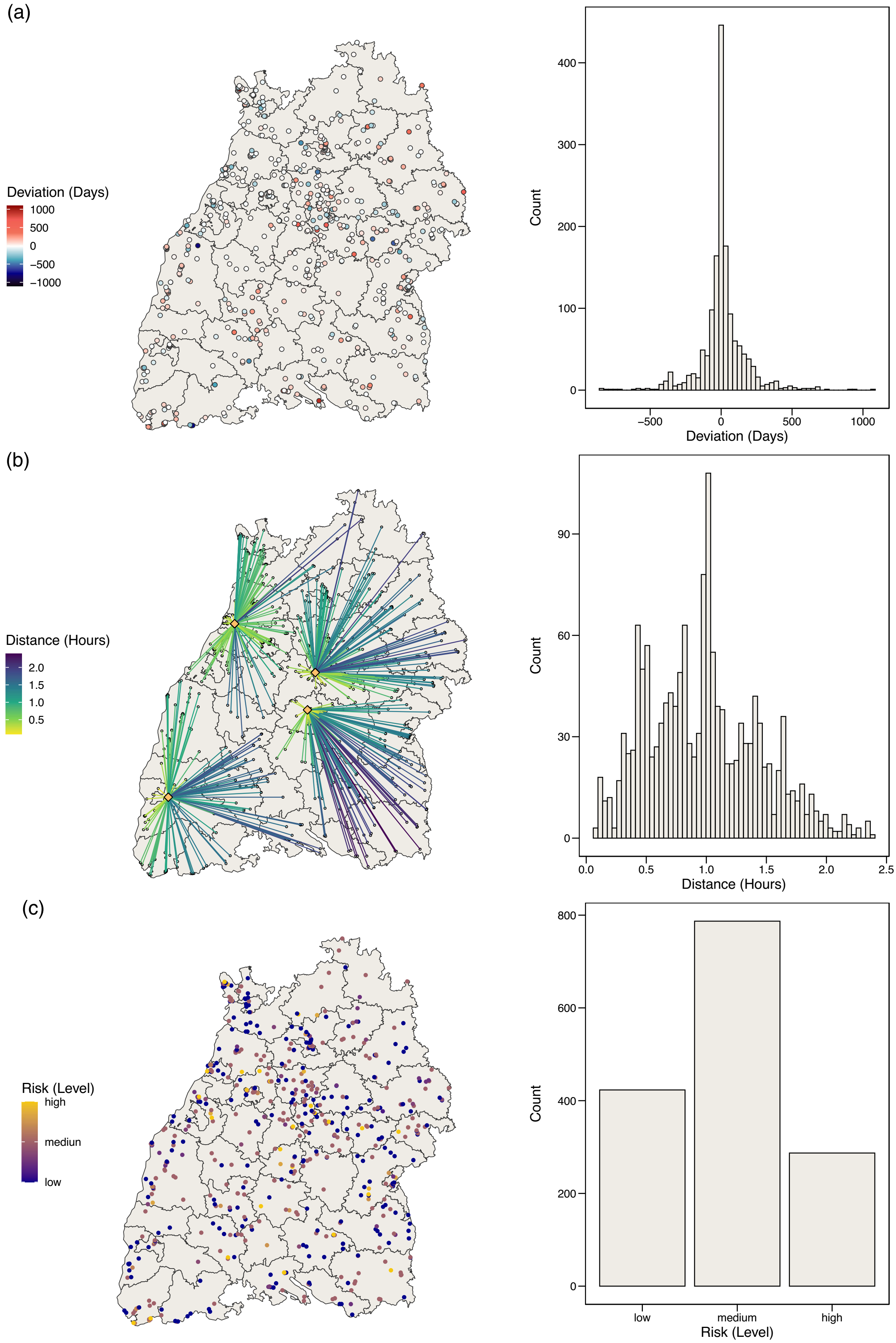

FIGURE 1 Spatial and numerical distribution of the dependent variable deviation (Days), and the independent variables distance (Hours) and risk (Level).

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deviate stronger positively (too late) than negatively (too early) from the inspection's legal due date. This can also be seen when looking at the mean value. The mean value indicates that, on average, inspections occur 9.58 days too late. Most of the observed delays are in a range between 0 and 500 days with only a few observations over 500 days. Besides the numerical distribution, the figure also shows the spatial distribution of the independent variable. Since our dataset contains multiple observations from the same locations, we took the mean deviation per location for this figure.

Furthermore, Figure 1b depicts the distance measured in hours between the district administrations located in Freiburg, Karlsruhe, Stuttgart, and Tübingen and the corresponding plant locations. Each line connects a location in our dataset with the responsible district administration. The colors of the lines correspond to the associated drive time with darker colors depicting longer drive times. Looking at the map lets us intuitively validate our estimate of drive time. Numerically, for our 1497 observations, both the median as well as the average drive time is around 58 min or 0.97 h. The average drive time varies greatly by district. For Karlsruhe, for instance, we find an average drive time of 0.79 h. In Tübingen, by contrast, inspectors have an average drive time of 1.26 h.

Finally, Figure 1c shows the distribution of the risk level. As stated before, plants can fall into three risk levels ranging from low to high. For the map, we averaged the respective risk on the location level. As Figure 1 shows there is no clear spatial pattern of the distribution of the risk level (for the relation between risk level and distance see Online Figure A4 in Appendix). Regarding the frequency, our dataset contains 287 observations from sites with high, 787 with medium, and 423 with low risk.

Model specification

To test the hypotheses, we estimate three sets of models. First off, we estimate three linear models with different specifications—one containing only the two main independent variables and one containing all variables, and one using all variables and the interval instead of the deviation as the dependent variable. All models have the following functional form:

$$Y_{it} = \beta_0 + \beta_1 Distance_i + \beta_2 Risk\,(high)_{it} + \beta_3 Risk\,(medium)_{it} \ldots + \varepsilon_{it}$$

All linear models are estimated using ordinary least squares (OLS). Furthermore, we use heteroskedasticity-consistent standard errors with HC3 as the estimator for the covariance matrix (MacKinnon & White, 1985). The standard errors are clustered on the plant level to account for the nested structure of the data. In all models, we could detect spatial autocorrelation in the residuals using Moran's I (Moran, 1950). To address this, we also estimate a set of spatial autoregressive (SAR) models. For these models, we add the spatially lagged dependent variable as an independent variable:

$$Y_{it} = \beta_0 + \rho W Y_{it} + \beta_1 Distance_i + \beta_2 Risk\,(high)_{it} + \beta_3 Risk\,(medium)_{it} \ldots + \varepsilon_{it}$$

The dependent variable Y_{it} is lagged according to the spatial weight matrix W. To define W, we must specify what kind of spatial dependencies we expect in the data. In our case, we would expect that locations close to one another should show more similarities than locations further apart. This could be the case as, for instance, there are some areas with higher shares of particularly environmental-friendly or litigious people that put pressure on the implementation authorities. Therefore, including the lagged variable allows us to account for unobserved spatial correlation in our data. The exact specification of *W* is described in Online Appendix A1. To estimate the SAR models, we rely on the spdep package in R (Bivand & Wong, 2018). The models are estimated using maximum likelihood (MLE). We also use heteroskedasticity-consistent standard errors with HC3 as an estimator of the covariance matrix (MacKinnon & White, 1985).

Lastly, we estimate a set of linear mixed-effect models. These models allow us to include random intercepts that capture finer-grained district-specific temporal variation and individual plant characteristics. The models are of the following functional form:

$$Y_{qit} = \beta_0 + Q_{0q} + I_{0i} + \beta_1 Distance_i + \beta_2\, Risk\,(high)_{it} + \beta_3 Risk\,(medium)_{it} \ldots + \varepsilon_{qit}$$

Q_{0q} represents random intercepts on the quarter district level while I_{0i} represents random intercepts for each plant individually. We estimate the models using the lm4 package in R. We obtain robust standard errors by utilizing a Wild-bootstrap with HC3 as the estimator for the covariance matrix.

Results

Figure 2 shows the resulting coefficient plots of the main independent variables for the six models with deviation as the independent variable. We include 90% (inner line) and 95% (outer line) confidence intervals. Table 1 shows the corresponding regression table for all models.

Under all specifications, we find a consistent positive effect of distance (driving hours) on the deviation from the inspections' legal due date. The effect is significant on the five percent in most models. Only in *Model 5* and *7*, we find slightly smaller p-values of around 0.07.

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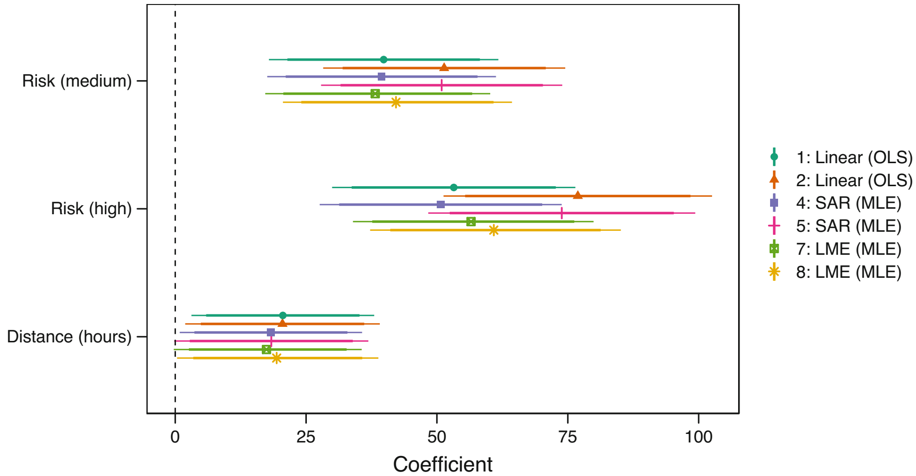

FIGURE 2 Coefficient plots for the main independent variables distance (Hours) and risk (Level). Estimate of the coefficients based on the regression models shown in Table 1. The bars indicate their respective 90% (inner) and 95% (outer) confidence intervals.

The coefficients identified range from 17 to around 21 days.[8] In other words, all things equal, an industrial plant located one hour away from the responsible authority gets inspected at least 17 days later—relative to the legal due date—than a plant directly at the authority location. This confirms our first hypothesis (H_1). Inspectors tend to prioritize industrial plants closer to their authority's location and thus more accessible and less time-consuming to reach and access.

But is this the only heuristic that guides the inspectors' actions? To answers this question, we can look at the risk level of the inspected plants. The risk level is determined based on an assessment of the sensitivity of the local surrounding or the potential consequences of accidents or exceptional circumstances. All models in Figure 3 show positive effects that are significant on the 1 percent level for medium- and high-risk sites relative to low-risk sites as the baseline category. Therefore, we can identify the effects with even higher confidence than H1. The coefficient sizes for high-risk sites range from 51 to 77 days and from 38 to 51 days for medium-risk sites. The finding is similar in the models with the inspection interval (as opposed to the legal due date deviation) as the dependent variable (*Models 3, 6*, and *9* in Table 1). For example, relative to low-risk sites, high-risk sites get inspected around 669 days earlier while based on the legal requirement the difference should be 730 days. Therefore, again, we observe a difference of at least 61 days.

Remarkably, this finding highlights that inspectors seem to prioritize controlling less risky over more risky plants. At this point, it is necessary to emphasize that this does *not* imply that high-risk plants are overall less frequently checked given that the legally prescribed inspection intervals are shorter in the case of high-risk compared to low-risk plants (low: every third year; medium: every second year, etc.). However, all things equal and again taking the most conservative estimate, a plant with a high risk would be inspected at least 51 days later and one of medium risk 38 days later—relative to the inspection's legal due date—than an industrial site of low risk. We thus find the exact opposite of what we expected initially and must reject our second hypothesis (H_2). Inspectors do *not* try to enhance the substantive impacts of their actions and to give precedence to riskier plants beyond what is legally required.

An alternative explanation for this finding could be that the longer inspection interval of lower-risk sites gives inspectors more leeway and discretion in planning their visits. There might be simply more opportunities to fulfill inspections on time or even early if the legally prescribed inspection interval is longer. Additionally, low-risk sights might be less burdensome to control, leading to another form of creaming for efficiency. We conduct a quantile regression in Online Appendix A7 to gain an insight into those alternative explanations. Instead of predicting the mean, quantile regression focuses on predicting the effect of the independent variables on different quantiles of the dependent variable. Regarding the risk level, our results indicate that the observed patterns stem from low-risk plants being controlled too early instead of high- or medium-risk plants being controlled too late. For the distance variable, by contrast, we see the exact opposite effect. Here, the quantile regression indicates that our distance variable has more explanatory power for higher than for lower quantiles. The drive time to the industrial site thus performs better in explaining the *late* inspections of more remote locations than the *early* inspections of closer ones.

Regarding the control variables, the involvement of local agencies in the inspection process does not make a significant difference. The commissioning of state-certified experts by the plant operator, in turn, reduces the length of the inspection interval by about two

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TABLE 1 Regression models.

DV	1: Linear (OLS) Deviation	2: Linear (OLS) Deviation	3: Linear (OLS) Interval	4: SAR (MLE) Deviation	5: SAR (MLE) Deviation	6: SAR (MLE) Interval	7: LME (MLE) Deviation	8: LME (MLE) Deviation	9: LME (MLE) Interval
(Intercept)	−41.59***	−162.35***	932.65***	−41.06***	−159.50***	925.50***	−46.64***	−68.40***	1026.60***
	(13.49)	(27.98)	(27.98)	(13.43)	(28.15)	(28.03)	(13.29)	(16.43)	(16.43)
Distance (hours)	20.57**	20.49**	20.49**	18.28**	18.35*	19.85**	17.43*	19.39**	19.39**
	(8.90)	(9.48)	(9.48)	(8.88)	(9.46)	(9.49)	(9.16)	(9.81)	(9.81)
Risk (high)	53.22***	76.92***	−653.08***	50.72***	73.85***	−656.20***	56.52***	60.87***	−669.13***
	(11.85)	(13.08)	(13.08)	(11.78)	(13.01)	(13.09)	(11.73)	(12.22)	(12.22)
Risk (medium)	39.82***	51.38***	−313.62***	39.43***	50.91***	−313.83***	38.21***	42.18***	−322.82***
	(11.18)	(11.79)	(11.79)	(11.14)	(11.75)	(11.77)	(10.96)	(11.16)	(11.16)
Workload		1.09***	1.09***		1.20***	1.11***		1.25***	1.25***
		(0.23)	(0.23)		(0.23)	(0.23)		(0.23)	(0.23)
Agent		−55.95**	−55.95**		−55.34**	−55.03**		−53.54**	−53.54**
		(23.94)	(23.94)		(23.90)	(24.01)		(24.72)	(24.72)
Agencies		29.20	29.20		31.53	32.41		18.48	18.48
		(24.76)	(24.76)		(24.67)	(24.73)		(24.46)	(24.46)
Sector dummies	×	✓	✓	×	✓	✓	×	✓	✓
Yearly dummies	×	✓	✓	×	✓	✓	×	×	×
RE: Plant							✓	✓	✓
RE: District:qtr.							✓	✓	✓
N	1497	1497	1497	1497	1497	1497	1497	1497	1497
N (plants)							801	801	801
N (district:qtr.)							102	102	102
(pseudo-)R^2	0.02	0.07	0.69	0.02	0.07	0.69	0.21	0.22	0.74
AIC	19457.80	19407.23	19407.23	19452.89	19401.16	19407.06	19388.62	19379.45	19379.45
BIC	19484.36	19497.52	19497.52	19484.76	19496.76	19502.66	19425.80	19448.50	19448.50

Note: Robust standard errors in parentheses (HC3), clustered (plant level) for models 1–3. Nagelkerke pseudeo-R2 for models 4–6, Nakagawa pseudo-R^2 (conditional) for models 7–9.
Abbreviations: LME, Linear mixed-effect model; MLE, Maximum likelihood estimation; OLS, Ordinary least squares; SAR, Spatial autoregressive model.
***$p < .01$.
**$p < .05$.
*$p < .1$.

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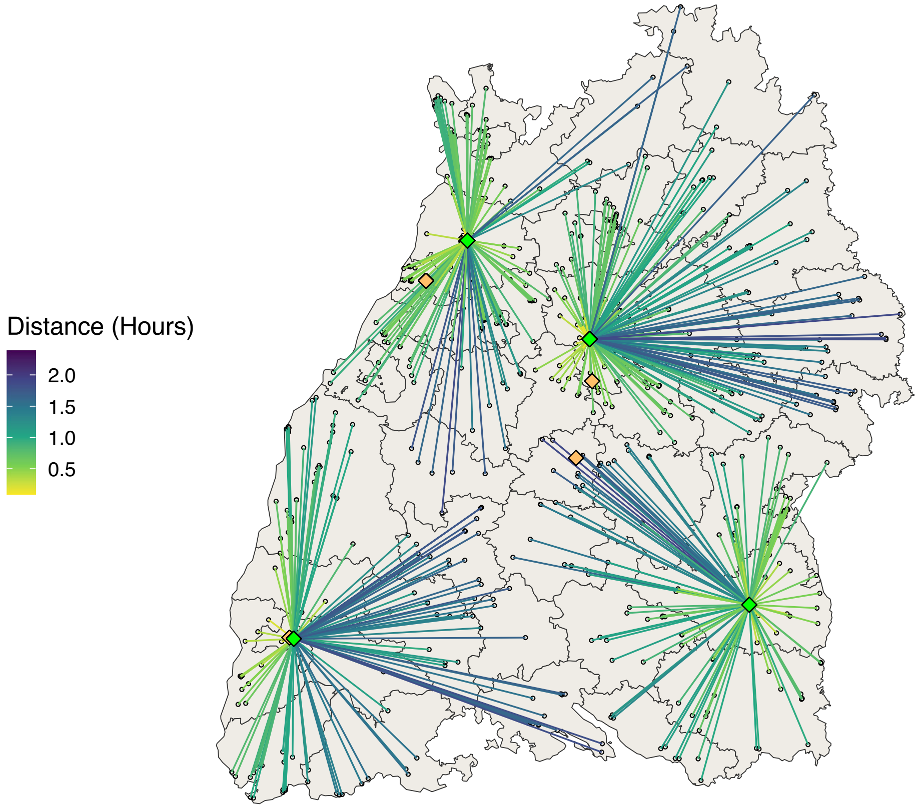

FIGURE 3 Optimal authority location based on the cumulative travel time per district. The yellow points mark the original authority location. The green points indicate the optimal authority location when the goal is to minimize the cumulative travel time. The lines represent the drive time from the optimal authority location to the locations of the industrial plants.

months. This speaks to the literature on "regulatory intermediaries" (Abbott et al., 2017), suggesting that the involvement of private sector actors and the establishment of "hybrid" regulatory regimes have the potential to improve policy implementation and enforcement. The current workload also shows significant effects. Each additional site that needs to be checked within a given period adds around one additional day of deviation. Beyond the workload, we also see that the random effects capture further temporal differences. For example, we find indications that the COVID-19 crisis has caused further delays in some districts (see Online Appendix A3).

Regarding robustness, our models show similar effects under *all* specifications of our dependent variables. While we find the effect of risk level with slightly higher confidence, distance still can be identified with high statistical certainty considering that the effect stays robust in specifications including district random effects as well as when accounting for spatial effects, both of which we would expect to affect the distance variable more than the risk level as the latter follows no spatial pattern. We test alternative explanations for the observed deviations such as duplicate visits in Online Appendix A6 and further model specifications in A5. Our results remain robust.

DISCUSSION: THEORETICAL AND PRACTICAL IMPLICATIONS

In the previous section, we have shown that front-line implementers develop coping practices to handle their workload. Specifically, we found that environmental inspectors tend to prioritize industrial plants that are close to the location of their authority and those that only pose a small risk to their environment. But what are the theoretical and practical implications of these findings?

From a theoretical perspective, the main difference between our analysis and previous insights on coping practices is that we find these patterns in the 'aggregate'. In other words, it is not only the single implementer who struggles and tries to individually find a way to deal with it. Rather, it seems that over time certain coping patterns become 'dominant' and occur *systematically* across multiple inspectors and inspections. Our case exhibits strong indications that the dominant coping pattern that emerges is one of creaming for efficiency. We deem these findings highly relevant for future research as, for instance, it might allow connecting (initial) 'micro' level observations such as implementers' coping practices to 'macro' level outcomes, such as organizational performance or policy impacts.

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From a practical perspective, our findings have different implications. Although alarming at first sight, we deem it overall less 'worrisome' that inspectors prioritize less risky over more risky plants. As discussed above, risk primarily drives the *too early* fulfillment of low-risk plants rather than the *too late* inspection of medium- or high-risk plants. Moreover, there also seems little room for optimization. The law already requires that high-risk plants are overall more frequently checked, given that the legally prescribed inspection intervals are shorter in the case of high-risk compared to low-risk plants. To determine the risk posed by an industrial plant, the administration uses a sophisticated scheme on the "Systematic Evaluation of Environmental Risks" (Government of Baden-Württemberg, 2013b). This scheme takes account of several pre-defined evaluation criteria to specify the exact risk level. In consequence, the risk level does not stay static over time but is constantly adapted based on new information, such as occurring violations. The designation of these risk levels can thus be considered a 'design-based' solution aimed at balancing the administration's workload and environmental security.

In contrast to our first key finding, our second finding reveals a significant effect of delayed inspections. Prioritizing inspections of nearby plants may ease the workload for those responsible for implementation, but it results in unequal protection for residents based on their location. According to Hanna and Oliva (2010), increasing the yearly inspection rate by one point (from zero to one, or from one to two inspections per year) reduces air pollutant emissions by approximately 11 percent.[9] Moving from the minimum (0.09 driving hours) to the maximum (2.4 driving hours) leads to a prolongation of the inspection interval by 39 days (17*2.31). This reduces the yearly inspection rate by a factor of 0.11 (39/365). Assuming that inspections have similar effects on other environmental quality factors, this means that industrial plants located far from the authority's location have a one percentage point lower potential per year to benefit from inspections than those located closer. Over time, these differences accumulate, leading to significant disparities in environmental quality between the center and the periphery.

But what could be done to address this 'uneven' policy implementation? While the observed coping patterns result from the inspectors' actions, these actions occur within the scope of the institutional possibilities and restrictions they encounter. It is a crucial insight from the 'synthesized' implementation literature that administrators make their decisions *locally* but within the scope of *centrally* determined factors (Matland, 1995, p. 149). For instance, our findings indicate that it might be beneficial to rely stronger on regulatory intermediaries and, this way, relieve the inspectors from some of their workload. Also, inspectors could be forced to randomly select from a pool of industrial plants they must inspect next. Such as a randomized selection process, however, must consider the fact that different plants pose different risks to the environment. Obviously, this is *not* impossible to achieve but requires a sophisticated calculation approach. Until now, the literature strongly recommends risk-based over random targeting but does not acknowledge that even *within* the scope of a risk-based approach, implementers possess sufficient leeway to implement policies 'unevenly' (Blanc, 2012). Likewise, it could help to change the shape of the jurisdictions and, this way, reduce the overall time and differences in the hours that inspectors must spend on the road. Although this might be often difficult, due to multiple implementation tasks that might demand different optimizations and historical legacies of district boundaries such as in our specific case.

One 'spatial' aspect that is easier to change, however, is the location of the implementation authority. While geographic relocations of public authorities are quite rare, they still occur occasionally and typically involve fierce political debate (Trondal & Kiland, 2010). Offering analytical tools might help to find 'objective' ways how to select the best location of public authorities and, this way, ease the discussion surrounding the issue. We start this exercise with the premise that implementation authorities *cannot* be located everywhere but, instead, need a decent level of infrastructure provision to attract highly skilled public sector employees and to guarantee easy travel to work. We thus restrict our analysis on medium-sized towns and cities. The full list of potential locations can be found in Online Appendix A8. In a second step, and in accordance with the prior analysis, we calculated the travel time between each of these potential authority locations and the industrial plants in the respective governmental districts. Thereafter, we identified the location with the smallest cumulative travel time. For this, we weigh the industrial sites differently based on their associated risk level. Thus, a high-risk site has a weight of three, a medium-risk site of two, and low-risk site has a weight of one. This weighting scheme allows us to derive the cumulative drive time associated with inspecting all plant sites in a time span of three years, where a low-risk site would be controlled once, a medium-risk site twice, and a high-risk one three times.

The results are presented in Figure 3. The green points indicate the optimal authority location when the central goal is solely to minimize the *cumulative* travel time to the industrial plants according to their weights.

The illustration shows that in the governmental districts of Karlsruhe and Stuttgart, the current authority locations are already quite close to the ideal points. Moving the authority would only reduce the cumulative travel time across three years by 37 h (12 percent decrease) and 11 h (3 percent decrease) respectively. In the case of Freiburg, even though the cumulative travel time is the highest across all existing district administrations, there is no potential for optimization. The most extreme difference can be seen in Tübingen. Moving the administration from Tübingen to Biberach could reduce the travel time by a total of 108 h (36 percent decrease). Considering that our

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estimated effect per hour driven was around 17 days additional deviation, a relocation bears the potential to reduce implementation deficits and delays substantially. Other weighting schemes that put (even) more emphasis on plants with a higher risk led to only minor relocation on the map compared to the optimal locations presented in Figure 3 (see Online Appendix A9 for a robust approach using a bootstrap procedure).

CONCLUSION

This paper has aimed to investigate whether (1) implementers apply systematic coping practices when handling their workload and (2) how these strategies look in practice. Focusing on the case of environmental enforcement, we found that inspectors primarily try to minimize the time-consuming and unproductive parts of their work. Moreover, they tend to prioritize low-risk over high-risk plants. In sum, inspectors thus seem to cream primarily for efficiency rather than for effectiveness.

This paper's second central insight is that the location of public authorities determines the implementation process. Our analysis revealed that inspectors systematically 'prefer' closer over more distant plants. This leaves citizens in the periphery with overall lower levels of environmental protection. Optimizing the spatial location of public authorities by reducing the average distance to the plants to be inspected has thus the potential to substantially reduce implementation deficits and delays. This finding is not limited to environmental protection but should apply to any enforcement activity where public implementers must perform on-spot visits, such as labor protection, animal welfare, or hygiene standards.

Our findings are remarkable as they are made in a setup that is not very prone to pronounced coping strategies and resulting implementation deficits. This implies that there is some chance that the observed patterns should be even more pronounced in other contexts. Yet, we have little knowledge about how inspectors behave elsewhere and whether the same considerations guide their actions. Future research might test our findings in different contexts. Here, it seems particularly promising to examine whether organizational features and corresponding levels (and forms) of political oversight make a difference in the choice of the coping practice pursued. In our case, the public authority responsible for enforcement is located at the state-level and under the direct control of the state government. In other areas, by contrast, IED enforcement activities are carried out by either a centralized environmental agency (see e.g., the Environmental Protection Agency in Ireland) or by local authorities (see e.g., the German state of North Rhine-Westphalia).

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DATA AVAILABILITY STATEMENT

The data and code used for the analysis are available under: https://doi.org/10.7910/DVN/JKARYN.

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ENDNOTES

[1] This argument rests on the observation that street-level implementers in, for example, social service delivery often deal with people in difficult life circumstances and might feel helpless if they cannot do more to support them due to time and resource constraints.

[2] They also provide a third subtype called cost efficiency, which can be considered the combination of the implementers' attempts to improve their quantitative *and* qualitative outputs. It implies that implementers do principally try to minimize their efforts but deviate from this general rule if the expected gains are 'worth' it.

[3] Please note that the terms 'qualitative' and 'quantitative improvement' are borrowed from the existing literature and connected to different types of creaming behavior. They do *not* imply that things are de facto getting better but that inspectors channel their energy and efforts to either increase their output (quantity) or the impact (quality) of their actions.

[4] Background interviews (Appendix A10) confirmed that the IED implied additional case- and workload that was not compensated by additional resources.

[5] In a recent survey performed on behalf of the German Federal Environmental Agency ('Umweltbundesamt') with state-level environmental inspectors, the interviewees suggested that ordinary inspections and those caused by reported (suspected) violations follow different logics and resource demand (Ziekow et al., 2018).

[6] https://cloud.google.com/maps-platform/routes.

[7] https://cloud.google.com/maps-platform/places.

[8] For the SAR models we additionally calculate the average direct and the average indirect effects using the impacts function in the spdep package (Bivand & Wong, 2018). The average direct effect is similar in interpretation to regression coefficients from linear regression.

[9] Remarkably, Hanna and Oliva (2010) find no effect of the (anticipated) threat of inspection on plant emissions. In other words, inspections actually must take place to make a real difference in the environment.

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