WORKING PAPERS

N° 1229

June 2021

"Water Quality, Policy Diffusion Effects and Farmers' Behavior"

Sylvain Chabé-Ferret, Arnaud Reynaud and Eva Tène

Toulouse School of Economics

Water Quality, Policy Diffusion Effects and Farmers' Behavior*

Sylvain Chabé-Ferret† Arnaud Reynaud‡ Eva Tène§

June 28, 2021

Abstract

The nitrogen cycle is one of the most disrupted geo-chemical cycles on earth. Human activity, mainly through intensive farming, releases nitrogen by-products such as nitrates and ammonium into the environment where they have wide ranging impacts on human health, biodiversity and climate change. One of the earliest and most ambitious regulations of nitrogen use in the world is the EU Nitrate Directive, which not only sets limitations on the amount and timing of nitrogen application but also makes the adoption of modern nitrogen management tools mandatory in an effort to enhance nitrogen use efficiency. We leverage the geographical and temporal variation in the implementation of the Nitrate Directive in France to estimate its causal effects on water quality, biodiversity and farmers' practices, productivity and profits in a Difference In Difference (DID) framework. We modify the DID estimator to account for the existence of diffusion effects along river streams, leveraging recent developments in the analysis of Randomized Controlled Trials over a network of interrelated units. This is a methodological extension that can be of interest for similar applications. We find that the EU Nitrate Directive reduced the concentration of nitrates in surface water by 1.23 milligrams per liter: a decrease of 8%. We find a clear dose-response relationship, with higher impacts where more of the upstream area is covered by the Directive. We also find that other biochemical indicators, as well as biodiversity, as measured by the number of fish and fish species, also improved as a result of the Directive. We also find that the Directive managed to improve farmers' nitrogen use efficiency and productivity and did not decrease their profits. These findings are consistent with the Porter hypothesis. Finally, we show that not accounting for diffusion effects biases downwards the estimate of the effect of the Directive obtained with a classical DID estimator and the more recent geographic discontinuity estimator.

Keywords: Policy Evaluation, Diffusion Effects, Water Pollution.

JEL Codes: D04, D80, Q01, Q25, Q53.

*We gratefully acknowledge financial support from the French National Research Agency (ANR) under the PENSEE project # ANR-16-CE32-0011 and the "Investissements d'avenir" program (Centre d'accés sécurisé aux données (CASD)) and from the Occitanie Region and Inrae. We thank the Observatoire du Développement Rural, especially Cedric Gendre and Eric Cahuzac for their generous sharing of time, expertise and data. We thank Saloua Benami, Rémi Bergès, Camille Calandre and Salomé Floderer for their outstanding research assistance. We thank Jennifer Alix-Garcia, Stefan Ambec, Matteo Bobba, Valentina Bosetti, Marshall Burke, Isis Durrmeyer, Habiba Djebbari, Meredith Fowlie, Ana Gazmuri, Kathrine von Graevenitz, Xavier d'Haultfoeuille, Céline Nauges, Peter Nilsson, Annie Ouin, Matthias Reynaert, François Salanié, Mohamed Saleh, Wolfram Schlenker, Ulrich Wagner; seminar participants at UMR SMART, UMR Economie Publique, MineParisTech and LSE Grantham; and participants at the 2019 AERE Summer Conference, 2019 NAERE workshop, 2019 EEA|ESEM conference, 2019 EAERE Summer School, 2019 and 2020 EAERE Conferences and 2021 Inrae workshop on water policies for fruitful discussions and comments. All remaining errors are our own.

†Toulouse School of Economics, INRAE, University of Toulouse Capitole, Toulouse, France and Institute of Advanced Study in Toulouse, Toulouse, France. Corresponding author: sylvain.chabe-ferret@tse-fr.eu.

‡Toulouse School of Economics, INRAE, University of Toulouse Capitole, Toulouse, France.

§Toulouse School of Economics, INRAE, University of Toulouse Capitole, Toulouse, France.

1 Introduction

The nitrogen cycle is one of the most disrupted geo-chemical cycles on earth (Rockstrom et al., 2009). During the past half century, the amount of nitrogen in the environment has increased more than that of any other element worldwide (Leach et al., 2012). Agriculture is the main source of nitrogen pollution. Of all nitrogen fertilizers applied on fields to increase crop yields worldwide, only 50% are actually absorbed by plants (Lassaletta et al., 2014). A significant amount runs off in river streams or evaporates into the atmosphere. Nitrogen by-products from agricultural sources have become the most pervasive chemical contaminant in the world's groundwater aquifers (WWAP, 2013). Air and water pollution by nitrogen by-products such as nitrates and ammonium have wide ranging impacts on human health, biodiversity and the climate (Galloway et al., 2003). Nitrogen by-products in water have impacts on human health, through methaemoglobinemia, a potentially fatal illness for infants causing the blue-baby syndrome (Lundberg et al., 2004). Nitrogen by-products also threaten aquatic biodiversity through the eutrophication process, an excess quantity of nutrients in waters, which creates algal blooms and dead zones (Canfield et al., 2010; Diaz and Rosenberg, 2008). In the atmosphere, nitrogen by-products are precursors of small particulate matter (PM2.5), which have been shown to increase the likelihood of respiratory and cardiac diseases. Finally, nitrogen, when it vaporises as nitrous oxyde, is a powerful greenhouse gas. The costs of pollution by nitrogen by-products are very high and reducing their presence in the environment is a key priority for governments around the world. The environmental and social costs of water pollution caused by agriculture have been estimated to exceed several billion dollars annually (OECD, 2012). The FAO considers that *"water pollution is a global challenge that has increased in both developed and developing countries, undermining economic growth as well as the physical and environmental health of billions of people."* (Mateo-Sagasta et al., 2017). The UN Environmental Program states that *"humans are producing a cocktail of reactive nitrogen that threatens health, climate and ecosystems, making nitrogen one of the most important pollution issues facing humanity"* (UNEP, 2019). It has launched a research initiative to improve management of the global nitrogen cycle, with the goal to halve the amount of nitrogen in the environment by mid-century. In this context, evidence of the effectiveness of policies aimed at reducing the amount of nitrogen by-products in the environment is sorely needed.

In this paper, we estimate the impact of one of the earliest and most ambitious regulations of nitrogen use in the world, the EU Nitrate Directive. The Nitrate Directive, enacted in 1991, required EU member states to delineate zones vulnerable to nitrate pollution and to enforce several regulations on the farming activities in these zones. The regulations under the Nitrate Directive include seasonal restrictions on the application of fertilizers, the planting of nitrate-fixing intermediate crops and grass buffer strips, and the building of storage facilities for manure. A very interesting feature of the Nitrate Directve is that it mandates the use of the nitrogen balance method by farmers with plots located in vulnerable zones, with the goal of increasing farmers' nitrogen use efficiency. The nitrogen balance method helps farmers determine the amount of nitrogen to apply on their plots as a function of the target yield and the amount of nitrogen remaining in the soil at the end of winter. The Directive therefore also requires farmers in vulnerable zones to perform soil analysis at the end of winter. The policy furthermore includes audits to control for farmers' effective enforcement with these requirements. The Nitrate Directive is a unique piece of regulation. No similar regulation exists in the U.S., for example. The Clean Water Rule enacted by the Environmental Protection Agency in 2015 and recently threatened by an executive order is of a much more limited scope.

We leverage the geographical and temporal variation in the implementation of the Nitrate Directive to estimate its causal effects on water quality and biodiversity, and on farmers' practices, nitrogen use efficiency, productivity and profits in a Difference In Difference (DID) framework. We study the effects of the implementation of the Nitrate Directive in France, one of the largest farming countries in the EU, which has severe nitrate pollution problems. Most of the Nitrate Directive regulation was implemented in France in 2001 in areas vulnerable to nitrate pollution. Vulnerable areas cover approximately 40% of France's territory and 70% of its utilized agricultural area.

We modify the DID estimator to account for the existence of diffusion effects along river streams. Because water flows along river streams, improvements in water quality due to the Directive might spill over downstream to areas not covered by the regulation. The existence of such spillover or diffusion effects belies a critical assumption that underlies most methods of causal inference, including DID.[1] In order to take diffusion effects into account, we leverage recent developments in the analysis of Randomized Controlled Trials in a network of interrelated units. We carefully define average treatment effects in the presence of diffusion effects as being the effects of treatment exposure, following Manski (2013) and Aronow and Samii (2017). The first key component of this approach is the existence of a matrix measuring the strength of connections between each units in the network. In our application, we build this matrix using data on upstream and downstream relationships along all France's river streams and watersheds. A second crucial component of this approach is the choice of an exposure mapping that, for each unit, assigns a level of exposure to the treatment as a function of the allocation of the treatment over the whole network. In our application, we use the proportion of upstream areas regulated under the Directive as our main treatment exposure indicator. We thus show that the average effect of treatment exposure is identified in a DID design under a set of sufficient conditions. These conditions include an equivalent to the classical assumption of parallel trends, which is testable using pre-treatment data. We also require that our definition of the exposure mapping is valid, which is much weaker than the assumption of an absence of diffusion effects. There futhermore needs to be some units that are not affected by the treatment at all. In our application, the existence of units unrelated to any other units, and of untreated units with no part of their upstream areas falling within vulnerable zones, ensures that this condition is actually met. In practice, we estimate the effect of treatment exposure using a parametric panel data model with a rich set of fixed effects. We also discretize our continuous treatment indicator in categories of increasing intensity, which enables us to test

[1] In technical terms, the absence of spillover or diffusion effects is generally called the Stable Unit Treatment Value Assumption and abbreviated as SUTVA (Imbens and Rubin, 2015).

for the parallel trends assumption and to measure a dose-response relationship non-parametrically. To account for autocorrelation between our measurements of water quality over space and over time, we adapt Leung (2020)'s estimator to panel data. To choose the adequate level at which to account for autocorrelation in Leung's estimator, we follow Barrios et al. (2012)'s suggestion to measure the extent of autocorrelation empirically. We also extend to panel data Athey et al. (2018)'s randomization-inference tests developed for the analysis of Randomized Controlled Trials in a network. This allows us to test for the existence of treatment effects at various distances and for the existence of a dose-effect relationship, accounting for the clustering of observations.

Our methodological extension of the DID estimator to interventions that have spillover effects on a network can be of separate interest for other applications for which Randomized Controlled Trials might not be feasible, but a source of spatial and temporal variation in treatment exposure exists. Diffusion or spillover effects affect multiple economic, social and biological phenomena such as water and air pollution, traffic congestion, the transmission of contagious diseases and the diffusion of innovations, to cite but a few. Our paper clarifies how treatment effects are to be defined in the presence of diffusion effects on a network under the DID assumptions, states conditions for their identification and provides ways to do inference on them. We also clarify the two key components of this approach: the proximity matrix and the exposure mapping. The proximity matrix might be the most critical component when applying our approach to other situations. In applications where interactions are mechanistic, because for example they stem from biophysical processes such as the diffusion of pollution along water or air flows, our approach can be applied straightforwardly. In other applications, especially characterized by behavioral interactions (such as migration or traffic, for example), our approach might require more modelling ex ante, for example by estimating a structural model and using it to define the proximity matrix. Our approach can then serve as a test for the predictions of the structural model.

In our application, to build our treatment exposure indicator, we combine data on upstream and downstream relationships along all of France's river streams and watersheds, with the map of vulnerable areas regulated under the Nitrate Directive. We then measure how surface water quality has changed over time between areas exposed to different levels of treatment exposure. We use measurements of surface water quality over the period 1994-2015 with more than 400,000 readings from 2,800 monitoring stations covering the entire French territory. Our measurements include physico-chemical outcomes such as concentrations of nitrates, nitrites, phosphorus, ammonium, along with dissolved oxygen and chemical oxygen demand, and biological outcomes such as the concentration in chlorophyll A, a proxy for eutrophication, the number of fish and fish species observed. We also investigate the impact of the Nitrate Directive on farmers' practices, productivity and profits using a more classical DID estimator and data from the French surveys of agricultural practices and from the Farm Accountancy Data Network (FADN).

We find that the EU Nitrate Directive reduced the concentration of nitrates in surface water in France by 1.23±0.27 milligrams per liter (mg/l), a decrease of 8%.[2] We find a clear dose-response

[2] We use the half-width of the 95% confidence interval as a measure of precision.

relationship, with higher impacts where more of the upstream area is covered by the Directive. The reduction in nitrate concentration that we measure goes from 0.05$\pm$0.30 mg/l when 25% to 50% of the upstream watershed is regulated under the Directive, to 0.73$\pm$0.41 mg/l when 50% to 75% of the upstream watershed is regulated, 1.37$\pm$0.43 mg/l when 75% to 99% of the upstream area is regulated, finally reaching 2.82$\pm$0.44 mg/l when 100% of the upstream watershed is regulated under the Directive. We also perform an heterogeneous analysis by seasons and hydrographic districts, and find that the largest drop in nitrate concentration occurs during winter, and in the Loire-Bretagne region (a region specifically concerned by nitrogen issues and algea blooms). We also find that the Directive improved the physico-chemical state of surface waters in terms of nitrites, ammonium, phosphorus, dissolved oxygen and chemical oxygen demand. Finally, we find a noticeable improvement in the biological state of rivers, thanks to the policy: chlorophyll A concentration significantly decreased by 2.7μg/l, the number of fish increased by 70 in the average monitoring station, and we find one additional species of fish in river streams regulated under the Directive. In addition, we show that wastewater treatment plants, climate and land use changes are unlikely to explain our results.

We find evidence that the Nitrate Directive successfully improved farmers' nitrogen management practices. We find that the policy increased the proportion of farmers: recording their nitrogen practices; measuring the amount of nitrogen remaining on their plots after winter; and adjusting their amount of nitrogen fertilizer using the nitrogen balance method. We also find that the policy increased by 6 percentage points (p.p.) the proportion of plots with nitrate-fixing intermediate crops, and decreased by 1.4kg/ha/year the amount of organic fertilizers applied on lands. We observe no impact of the Nitrate Directive on the planting of grass buffer strips, which can be explained by the fact that they were made mandatory throughout Europe as a pre-requisite for the granting of subsidies under the first pillar of the Common Agricultural Policy. More surprisingly, we do not find that the policy changed the amount of mineral nitrogen fertilizers applied on plots. Nevertheless, we find that the Nitrate Directive improved the efficiency of nitrogen fertilizer use. The indicator of nitrogen use efficiency, which measures the ratio of nitrogen output to nitrogen input, increased by 16$\pm$7 p.p. and the *N balance* indicator, estimating nitrogen loss to the environment, has significantly dropped in treated areas (-9$\pm$6.6 p.p.). Hence, the nitrogen content of harvested crops has increased by 7%. Our results suggest that the technological standards imposed by the regulation have triggered significant changes in farmers' behavior by disclosing information on when and how to apply fertilizers, thus ensuring productivity gains. Consistent with that assumption, we find that the variance of nitrogen application has increased in areas covered by the Nitrate Directive. This confirms that farmers are adapting their choices of fertilizer quantities to the specific needs and characteristics of their crops and fields. As a consequence, we find evidence that the regulation increased farmers' total factor productivity, suggesting that the mandated adoption of improved fertilization practices did indeed trigger productivity increases. Overall, these results are compatible with the Porter hypothesis that environmental regulation might increase the productivity of regulated agents (Porter and Van der Linde, 1995).

Finally, we find that the classical DID estimator that does not account for the existence of diffusion effects would have obtained smaller estimates of the policy impact. This downward bias is not very large though because, in our application, most areas that are downstream of a regulated area are also regulated. We also find that a classical DID estimator would have underestimated the steepness of the dose-response relationship, and therefore would not have captured how much larger the effects of the regulation are when a bigger share of the upstream watershed is regulated. Lastly, we find that the most recent geographic discontinuity estimators of the effect of regulation on water pollution such as the one proposed by Keiser and Shapiro (2017) would also have underestimated the effect of the Directive and of the dose-response relationship. It would also have provided less precise estimates than our proposed method. This makes sense because, since nitrates pollution is due to the combined action of multiple small emitters, studying the impact of the Directive by observing how pollution changes when we cross the borders of the regulated zone has limited power. Using a continuous measure for treatment exposure enables us to leverage the natural variation in the proportion of upstream areas regulated under the Directive as a source of identification for its impact.

Our paper contributes to several literatures. On the methodological side, our paper clarifies the definition, identification, estimation of and inference for causal effects in the presence of diffusion effects on a network under the DID assumptions. We draw heavily on recent developments in the literature on the analysis of Randomized Controlled Trials over a network, especially Manski (2013) and Aronow and Samii (2017) who introduce the overall setting and define the concept of treatment exposure and the assumption of a properly specified exposure mapping, Leung (2020) who introduces an estimator for doing inference with treatment effects on a network, Athey et al. (2018) who propose randomization inference tests for various features of treatment effects with interactions over a network and Barrios et al. (2012) who propose a set of best practices to account for clustering in DID regressions. To our knowledge, our paper is the first to delineate a full set of sufficient conditions for the identification of treatment effects over a network under the DID assumptions. Delgado and Florax (2015) propose a linear model with a spatial contiguity matrix in a DID model, and analyze its behavior in Monte Carlo simulations. Manresa (2016) proposes to uncover the proximity matrix using machine learning on panel data relating outcomes to a time-varying treatment. She nevertheless assumes away time fixed-effects, thereby eschewing one of the main components of a DID setting. Our paper is also closely related to Borusyak and Hull (2021) who propose an approach to estimate the effect of non-random exposure to exogenous shocks. One of their suggested applications is the analysis of exposure on network data. Our approach is complementary to theirs: instead of leveraging the random part of the exposure and correcting for the non-random part using randomization inference, as they do, we directly invoke a parallel trends assumption. Our approach to defining treatment effects in the presence of diffusion effects is reminiscent of Miguel and Kremer (2004) and Cai et al. (2015), where the proportion of neighbors assigned to a treatment is used as an indicator of treatment exposure, and of Banerjee et al. (2013) where network centrality is used to proxy for treatment effectiveness. In the context of DID, the closest papers to ours are Imbert and Papp (2020), where the proportion of migrants from a given rural area is used to proxy for the intensity of the indirect effect of a job guarantee program, and Deryugina et al. (2019) and Missirian (2019), who use the upwind/downwind relationship between counties to account for the spillover effects of air pollution.

We also contribute to the literature estimating the impact of environmental regulation on the environment. Most of this literature has looked at regulations affecting air quality. Among the papers studying water quality, some estimate the impact of water quality on the environment or human health, without looking at the effect of specific regulations (Ebenstein, 2012; Brainerd and Menon, 2014). Greenstone and Hanna (2014) estimate the impact of water pollution regulations in India without accounting for diffusion effects along river streams. More closely related to us, Keiser and Shapiro (2017) use individual station data to estimate the impact of the U.S. Clean Water Act on surface water quality. Their approach relies on the point-source nature of the Clean Water Act. They use the installation of a new wastewater treatment plant as a treatment, and identify its causal effect by comparing the ways in which water quality just above and just below the plant changes after the treatment. Similarly, He et al. (2020) use local comparisons between plants located upstream and downstream of pollution monitors to estimate the impact of regulation on TFP. Other empirical studies that consider the impact of regulation on non-point source water pollution combine a structural model of farmers' choices with a reduced form model relating those choices to water quality. This approach enables above all the study of the impact of monetary incentives such as taxes (Lungarska and Jayet, 2014) or payments for environmental services (Wu et al., 2004) but not the impact of a command-and-control policy such as the E.U. Nitrate Directive, the behavioral effects of which are much harder to model a priori. In this approach, the impact of agricultural practices is estimated using an explicitly spatial model, and sometimes an upstream-downstream weighting matrix (Bayramoglu et al., 2019). The key difference with our approach is that these models are estimated using a random effects specification which assumes that permanent unobservables are uncorrelated with treatment exposure, whereas we use a fixed effects approach that allows for an arbitrary correlation between unobservables and treatment exposure. While the random effects specification might be defensible when looking at the effects of land use on water quality (thanks to a rich set of control variables), it is clearly not suited to policy evaluation when the regulation is correlated with the level of pollution ex-ante.

Finally, our results are also related to the literature on the impacts of environmental regulation on companies' performance. We find evidence that the EU Nitrate Directive has not had detrimental consequences on farmers' profits, and evidence of an increase in total factor productivity. Our results are thus compatible with the Porter hypothesis stating that environmental regulation might trigger innovation and productivity growth in the regulated firms (Porter and Van der Linde, 1995; Ambec et al., 2013). Greenstone et al. (2012) find similar results for one out of the four substances regulated under the U.S. Clean Air Act Amendments. Similar positive effects have been found for the EU Emissions Trading Scheme by Barrows et al. (2021) and Pavan et al. (2019). Not all regulations have positive effects on regulated firms. For example, He et al. (2020) find that monitored firms see a decrease in productivity of 25%. In our application, though, we can delineate a credible causal channel through which the regulation improved farmers' productivity, namely the adoption of more efficient nitrogen management techniques.

The paper is structured as follows. Section 2 provides a background discussion on anthropogenic nitrogen pressures and the Nitrate Directive. Section 3 describes the data sources. Section 4 sets out the methodology. Section 5 presents the results and Section 6 discusses them. Section 7 concludes.

2 The Nitrogen Cycle and the EU Nitrate Directive

In this section, we first present the natural nitrogen cycle and how it has been disrupted by human activities. We then present the details of the EU Nitrate Directive.

2.1 The Nitrogen Cycle and Human Activities

The Nitrogen Cycle Nitrogen is the fifth most abundant element on our planet. It is essential to life, as a basic constituent of proteins and DNA. Nitrogen is converted into multiple chemical forms such as nitrate (NO_3^-), ammonium (NH_4^+), nitrite (NO_2^-), nitrous oxide (N_2O), nitric oxide (NO) or nitrogen gas (N_2) as it circulates in water, air and soil, through a biogeochemical cycle called the nitrogen cycle (EU Nitrogen Expert Panel, 2015). The most abundant form of nitrogen is nitrogen gas, the main component of the earth's atmosphere. Nitrogen gas is a highly stable and non-reactive molecule that very few organisms can use as a source of organic nitrogen. Therefore, plants cannot directly extract nitrogen from the atmosphere–unlike with carbon–but can only absorb it in a reactive form such as nitrate or ammonium. The natural production of reactive forms of nitrogen is mostly due to the fixation of nitrogen gas by highly specialized bacteria. As the natural regeneration of reactive nitrogen is extremely slow, nitrogen has long been a major factor limiting plant yields and population growth (Smil, 2000).

Human-Induced Changes to the Nitrogen Cycle The invention of the industrial synthesis of ammonium by Friz Haber and Carl Bosch at the beginning of the 20$^{\text{th}}$ century provided humankind with a cheap and reliable source of reactive nitrogen (Smil, 2000). Canfield et al. (2010) report that from 1960 to 2000, nitrogen fertilizer use increased by around 800%, primarily on wheat, rice and maize. As a result, crop yields skyrocketed, and Haber and Bosch's invention is sometimes claimed to be responsible for the doubling of the human population (Erisman et al., 2008). Today, half of all the nitrogen present in human bodies is estimated to come from the Haber-Bosch process (Erisman et al., 2008) which is also responsible for 2% of the world's annual energy use (Smil, 2000).

Inefficiencies in the conversion of nitrogen at several points of the food production cycle have raised the amount of reactive nitrogen in the environment. First, the conversion of nitrogen fertilizer into crops is far from perfect. Worldwide, on average, less than 50% of nitrogen applied on fields is absorbed by plants (Lassaletta et al., 2014). Second, the conversion of plant nitrogen into animal nitrogen is also ineffective, resulting in emissions of reactive nitrogen by cattle in the form of manure. Third, the same inefficiencies occur when humans transform plant or animal proteins into human proteins. As a consequence, the majority of reactive nitrogen applied to fields ends up in the environment, either running off in river streams or evaporating into the atmosphere.

Air and water pollution by reactive nitrogen such as nitrates and ammonium have wide-ranging impacts on human health, biodiversity and the climate (Galloway et al., 2003). In water, reactive nitrogen has impacts on human health through methaemoglobinemia, a potentially fatal illness for infants that causes the blue-baby syndrome (Lundberg et al., 2004). Reactive nitrogen also threatens aquatic biodiversity through eutrophication (Canfield et al., 2010; Diaz and Rosenberg, 2008). Eutrophication occurs when anthropogenic nutrients (mainly nitrogen and phosphorus) flow into waters, causing the proliferation of algae whose decomposition induces a loss of oxygen. This in turn asphyxiates aquatic life and might result in dead zones, that is, areas where biodiversity has decreased severely. Eutrophication arises during springtime and summertime when higher temperatures and luminosity increase algae growth. In the atmosphere, reactive nitrogen is a precursor of small particulate matter (PM2.5) which has been shown to increase the likelihood of respiratory and cardiac diseases. Finally, reactive nitrogen is also a powerful greenshouse gas when it vaporizes as nitrous oxide.

2.2 The EU Nitrate Directive

In this section, we first present the general setting of the EU Nitrate Directive before detailing the way it has been implemented in France.

General setting of the EU Nitrate Directive In 1991 the European Union implemented the Nitrate Directive, one of the world's earliest and most ambitious attempts to regulate nitrogen use. The Nitrate Directive mandates EU Member States to delineate zones vulnerable to pollution by nitrates. Within these zones, it sets up a set of requirements for nitrogen management. Figure 1 shows a historical timeline of the policy with the detailed sets of measures as they have been implemented in France.

The Nitrate Directive is designed to reduce the amount of reactive nitrogen in the environment, mainly in three ways: *(i)* by making the building of storage facilities for manure mandatory and setting limits on the amount of nitrogen fertilizer and manure that farmers can apply on fields; *(ii)* by requiring the adoption of technical innovations to increase nitrogen use efficiency; and *(iii)* by requiring the adoption of techniques reducing the amount of nitrogen runoff from fields (*i.e.* planting of nitrogen-fixing crops during winter and of grass buffer strips along river streams). The Nitrate Directive requires above all not only that farmers record their fertilization practices, but also that they adopt the nitrogen balance method. The nitrogen balance method is an agronomically-founded method that helps farmers determine the amount of nitrogen to apply on lands as a function of the target yield and the amount of nitrogen remaining in the soil at the end of winter. The policy also requires that farmers conduct soil analysis on their farms to estimate the level of nitrogen present after the winter. The nitrogen balance method aims at improving nitrogen use efficiency by reducing the amount of nitrogen applied to fields when it is not needed (when nitrogen from the previous crop is left in the soil after winter). The nitrogen balance method also helps farmers determine how much nitrogen to apply to a field, depending on the type of crop and of their target yield.

The Nitrate Directive furhtermore includes randomly performed audits on farms to check for compliance with the regulation. Farmers have to pay a fine in case of non-compliance (from €1,500 to €3,000 in case of recidivism).

The EU Nitrate Directive in France The Nitrate Directive was transposed into French law in September 1993. Vulnerable zones are defined as areas in which surface and ground waters have a nitrate concentration higher than 50 mg/l or between 40 mg/l and 50 mg/l with no improvement trends and/or showing signs of eutrophication linked with intensive agriculture. The data used to define the position with respect to these thresholds was data collected before 1993. The map of vulnerable zones stabilized around 2000, with very little evolution afterwards; the area covered by vulnerable zones increased by less than 7% after 2002. Figure 2 shows a map of the evolution of vulnerable zones from 2000 to 2015.

In France, the first set of measures under the EU Nitrate Directive were implemented between 1997 and 2000 as the first action program (see Figure 1). This was a minor program that mainly concerned nitrogen application standards, and that was used primarily to prepare farmers for compliance in 2001. Our analysis thus focuses on the following action programs and uses 2001 as the treatment year. In our main specification, we include all the time periods (vulnerable zones of 2000, 2003, 2007 and 2012) and analyze them as if treatment started in 2001 for all of them. This might bias our estimates downwards since we consider as treated in 2001 some zones that would only be treated later. Since those zones account for only a small portion of all the treated zones, we expect this bias to be small.[3]

3 Data

In this section, we describe the data that we use to estimate the impact of the Nitrate Directive on water quality and on farmers' practices, profits and productivity in France. We first detail the data we use to build treatment exposure. We then move on to data on water quality and we end by presenting the farm-level data that we use.

3.1 Data on vulnerable areas and on the hydrographic network

We use data on the French hydrographic network from the French National Geographic Institute to have information on upstream-downstream relationships for each river making up the network.

[3]We choose to focus on 2001 as our sole entry date in order to avoid the issue of negative weights in fixed effects estimators for Difference-In-Differences with staggered entry date (Athey and Imbens, 2021; Borusyak and Jaravel, 2017; Callaway and Sant'Anna, 2020; de Chaisemartin and D'Haultfœuille, 2020; Goodman-Bacon, 2021; Sun and Abraham, 2020). The fact that most of the vulnerable zones start to be treated in 2001 makes this approach viable. Section 5.3 tests the robustness of our estimates to this assumption.

The hydrographic network of mainland France is composed of 6,108 hydrographic zones that are designed to follow the courses of the main river streams. Figure 3a shows the whole network of French main river streams. Figure 3b shows the 6,108 hydrographic zones that cover the whole French metropolitan territory. Each hydrographic zone is defined as a watershed: an area containing portions of rivers and groundwaters where precipitations collect and flow into a common outflow. The hydrographic zone is the finest scale of catchment area available from the hydrographic data. Each hydrographic zone is part of a network of similar zones that form an arborescence. The French hydrographic network is organized into 127 such arborescences. Each arborescence is composed of at least one upstream watershed, *i.e.* the water source, a chain of intermediate watersheds, and a downstream watershed through which freshwater flows into the ocean or the sea. Figure 3c shows part of such an arborescence.

We merge the map of hydrographic zones shown on Figure 3b with the map of vulnerable areas shown on Figure 2, that we have retrieved from the French government website (data.gouv.fr), using GIS software. We compute the area of each hydrographic zone covered by the Directive at any time period between 2000 and 2012 as our measure of the extent to which each hydrographic zone is treated.

3.2 Data on water quality

We measure the impact of the Nitrate Directive on surface water rather than on ground water. We anticipate that the policy will have more detectable effects on the quality of surface water compared to ground water where nitrogen accumulates. Additionally, the biodiversity impacts of reactive nitrogen are mostly felt in surface water.

We use data on surface water quality from the French public service Eau France compiled in the national data interface Naïade. These data are produced by a countrywide network of stations all along France's river streams, that monitor water quality. In practice, government officials from each Water Agency and the French Biodiversity Agency periodically visit each monitoring station to collect water for analysis and to collect biological data on site.

We track water concentrations in reactive nitrogen, mainly nitrate, ammonium and nitrite. We also measure the concentration in phosphorus, which is generally applied to fields at the same time as nitrogen. We proxy for eutrophication using the concentration in Chlorophyll A, which is a good estimate of the amounts of algae present in the water. We also use chemical oxygen demand, which measures how much organic matter is in suspension in the water in relation to how much oxygen is required for its decomposition, and the concentration of dissolved oxygen. Large chemical oxygen demand signals that eutrophication is present, whereas large concentrations in dissolved oxygen signal that eutrophication is not severe. Finally, we use the number of fish and the number of different species of fish in the water as measures of biodiversity.

Monitoring stations have been measuring the quality of surface water in France since 1971. The number of analyses per monitoring station actually sharply increased with the enactment of the Nitrate Directive in French Law in 1993. We therefore focus on the period 1994-2015 in ou rmain empirical analyses. We select data from monitoring stations that have measurements over at least 5 years, and with at least one measurement before 2000. The resulting dataset is a panel of 2,800 monitoring stations with more than 400,000 water quality readings. Figure 4 shows a map of the monitoring stations included in the final dataset along with the map of the French watersheds.

To control for any annual or monthly variations in water quality due to weather conditions, we use a database from Météo France providing us with information on monthly average temperatures and precipitations over the period under study: 1994-2015.

3.3 Data on farming practices and profits

To measure the impact of the Nitrate Directive on farmers' practices, profits and productivity, we use three separate datasets: the survey on farming practices, the agricultural census, and the Farm Accountancy Data Network (FADN).

The survey on farming practices records detailed information on farmers' agricultural practices on a representative sample of fields. The sample is built to be representative of the farming practices with regard to the main crops planted in France in a given year: durum wheat, soft wheat, barley, grain maize, forage corn, rape, sunflower, peas, beet and potato. For each crop, a set of points is selected at random within the départements where the crop accounts for more than 10% of the overall area dedicated to that same crop nationwide.[4] Enumerators visit the farmers cultivating the plots to which each selected point belongs and record all the farmers' interventions made (soil preparation, seeding, fertilization, pesticide use, yields, etc). Surveys on farming practices were conducted in 1993, 2000, 2005 and 2010. Since each point does not exhibit the same crop each year, the survey of farming practices is a repeated cross section and not a panel. Because the set of crops and of départements changes from year to year, we have built a sample where each crop and département pair appears every survey year.

From the survey on farming practices, we extract an array of outcomes that might have been impacted by the Nitrate Directive. We first look at N, the amount of mineral nitrogen fertilizers applied on plots (expressed in kg/ha/year), P, the amount of mineral phosphorus fertilizers applied on lands (in kg/ha/year) and at $Manure$, the amount of organic fertilizers applied on lands (in kg/ha/year). Second, we build indicators of nitrogen use efficiency, following Brentrup and Lammel (2016). N_{input} measures the nitrogen content of all the inputs applied by the farmer to fertilize the plot, including especially N and $Manure$. N_{input} is computed by multiplying the quantity of each input by its actual nitrogen content. For manure, we use conversion tables provided by AgroParisTech. N_{output} measures the nitrogen content of the outputs extracted from the field. N_{output} is computed by multiplying the crop yield by the nitrogen content of each crop. We use conversion tables specific to each crop provided by the COMIFER. Finally, we build two indices of nitrogen productivity. nitrogen use efficiency, NUE, is the ratio of N_{output} to N_{input}. NUE measures the efficiency of mineral and organic nitrogen conversion into nitrogen contained in crops. We also compute the balance of nitrogen on the field, $N_{balance}$. $N_{balance}$ is the difference between

[4]Départements are the second largest administrative unit in France. There are 95 départements in France.

N_{input} and N_{output}. It measures how much nitrogen has been extracted from the field by the crops, net of how much has been input through fertilization. A positive $N_{balance}$ means excess nitrogen that might run off the field.

The survey on farming practices also collects information on whether farmers estimate the amounts of nitrogen remaining in the soil at the end of winter and whether they use the nitrogen balance method to estimate the amount of nitrogen to apply on the plot. We generate two dummy variables: $N_{estimated}$ and NBM. $N_{estimated}$ takes value one when the farmer measure nitrogen at the end of winter and zero otherwise. NBM takes value one when the farmer use the Nitrogen Balance Method and zero otehrwise. The survey on farming practices also collects data on farmers' adoption of practices aiming at curbing nitrogen runoffs from fields. Nitrate-fixing intermediate crops are planted between winter and spring to avoid nitrogen runoffs by fixing nitrogen in their biomass. Grass buffer strips are strips of land along river streams that are permanently covered by vegetation to avoid nitrate discharges from agricultural fields. We form two dummy variables taking value one when the farmer has planted a nitrate-fixing intermediate crop or a grass buffer strip on her field.

To measure the effect of the Nitrate Directive on profits and productivity, we use data from the Farm Accountancy Data Network (FADN), an 8-year rotating panel of professional French farms. The FADN has detailed accounting information, especially on spending on inputs and on the value and quantity of outputs. From the FADN, we form several types of outcome variables. First, we use data on spending on input use, especially fertilizer. We cannot separate spending on nitrogen fertilizers from spending on phosphorus and potassium fertilizers, but nitrogen fertilizers account for most of the money spent by French farmers on fertilizers. We measure overall spending on fertilizers and spending per hectare of crops and per hectare of usable agricultural area. Second, we use data on spending on services for crops, which contains spending for lab analysis of the soil nitrogen content mandated by the Nitrate Directive. Third, we compute yields by dividing the quantity produced by the area dedicated to each crop. We standardize yields using their yearly mean and standard deviation. Fourth, we compute data on gross margin and value added at the farm level by taking the value of crop production and subtracting from it spending on various items of intermediate consumption (fertilizers, seeds, pesticides, services, etc.). Fifth, we compute an index of total factor productivity. We use a ratio between the value of output and a Cobb-Douglass combination of the value of inputs (intermediate consumption, labor and capital (including land)), as suggested by Syverson (2011). The weights used for weighting the values of inputs are the average factor shares over the whole period. The factor shares are computed as the share of total spending spent on each factor. As suggested by Syverson (2011), we compute capital spending as a residual after subtracting spending on intermediate consumption and labor from total spending. One particuilarity of agriculture is that spending on labor does not include the farmer's labor or that of their family. To include the farmer's labor and that of their family in the amount of labor used on the farm, we convert the time spent working on the farm (which is reported on the FADN) into monetary terms based on the nominal wage of a blue-collar worker in

France, provided by the French National Statistical Agency (INSEE).

Finally, we use data from the agricultural censuses of 1988, 2000 and 2010 to measure the amount of land dedicated to each crop in vulnerable and non-vulnerable areas. The French national agricultural census surveys all farms in the country every ten years and collects detailed information on land use in the year of the census.

We identify whether each farm or plot in the surveys that we use belongs to a vulnerable zone by using the geocoded information that we have on them and merging it with the map of vulnerable zones shown on Figure 2. For the French national agricultural censuses and the FADN, we are able to locate farms at the commune level. The commune is the smallest administrative unit in France, with an average size of 15 square kilometers, 200 times smaller than the average U.S. county. We thus locate each farm at the centroid of the commune to which it belongs before merging it with the map of vulnerable zones. For the survey of farming practices, we directly use the geographical coordinates of each plot in order to locate it within or outside a vulnerable zone.

Table 1 presents descriptive statistics from the resulting dataset. Farms in vulnerable areas are slightly larger than farms in non-vulnerable areas, but this difference does not change much over time. Nitrate-fixing crops were almost absent before 2001,yet cover 10% of all plots afterwards, but only in vulnerable areas, which suggests a causal impact of the Nitrate Directive. Grass-buffer strips do not follow the same pattern: their presence increases in both vulnerable and non vulnerable zones at the same pace. N and P, the quantities of nitrogen and phosphorus mineral fertilizers applied to fields, are similar in both zones and in both time periods, which surprisingly suggests that the policy might not have had an impact on the amount of mineral fertilizer. In contrast, the quantity of organic fertilizer decreases more in vulnerable areas after 2001, suggesting a possible impact of the Nitrate Directive. Perhaps the most impressive differential evolution recorded on Table 1 is the massive increase in N_{output} observed within vulnerable zones, while it remains constant in non-vulnerable zones. Together with the fact that N_{input} varies in the same way in both zones, this implies that $N_{balance}$ improves and that nitrogen use efficiency increases in vulnerable zones. The accounting data from FADN broadly confirm these results. They suggest that, although spending on fertilizers increased slightly more in vulnerable areas than in non-vulnerable ones, the value of production increased even more, whereas spending on other factors remained broadly similar in both vulnerable and non-vulnerable zones. As a consequence, total factor productivity seems to have increased more in vulnerable areas than in non-vulnerable ones. Whether these changes are actually caused by the policy requires more investigation.

4 Methodology

In this section, we present the econometric methodology that we use to infer the causal effect of the Nitrate Directive on water quality and farmers' practices and productivity. Since the Nitrate Directive was implemented on a subset of the total French area (roughly 40% of the total area of metropolitan France and approximately 70% of its usable agricultural area) after 2001, we use a Difference In Difference (DID) framework to estimate its causal effect. Because water flows along river streams, improvements in water quality due to the Nitrate Directive being implemented in vulnerable areas might spill over to non-vulnerable areas located downstream. The classical DID estimator that ignores the upstream/downstream relationships between hydrographic zones will thus be biased downwards. We modify the DID estimator to account for potential spillover effects of the Directive, leveraging recent developments in the definition and estimation of, and inference on, treatment effects in the analysis of Randomized Controlled Trials on a network of interrelated units. This methodological extension to DID might be of interest for similar applications. In the remainder of this section, we first detail our approach for dealing with diffusion effects on a network in a DID framework, and expain how we apply this approach to estimate the effect of the Nitrate Directive on water quality. We then detail how we estimate the effect of the Directive on farmers' practices, where we use a much more classical DID approach.

4.1 Estimating the effect of the Nitrate Directive on water quality

In this section, we set out our approach to define, estimate and do inference on treatment effects in a DID design when there are diffusion effects. To this end, we leverage recent developments in the analysis of Randomized Controlled Trials over a network of interrelated units. We illustrate each step by detailing how it applies to the estimation of the impact of the Nitrate Directive on water quality. We first start with the basic setting that enables us to define treatment exposure and its average effect. We state conditions for the identification of the effect of treatment exposure in a DID setting and then proceed with estimation of and inference on this parameter. We end up with randomization-inference tests of the existence and shape of the effects of the regulation on water quality.

Setting

Our approach closely follows Manski (2013) and Aronow and Samii (2017). We simply allow for panel data and the existence of periods where the treatment is absent.[5] We assume access to a population of N units $i = \{1, \ldots, N\}$ observed over T time periods $t = \{1, \ldots, T\}$. In our application, units are hydrographic zones. Each unit i belongs either to the treatment group, which we denote as $D_i = 1$, or to the control group, which we denote as $D_i = 0$. In our application, D_i indicates whether a hydrographic zone belongs to a vulnerable zone or not. The membership of the treatment group in the whole population can then be characterized by a treatment group vector $\mathbf{D} = \{D_1, \ldots, D_N\}$. $\mathbf{\Omega} = 2^N$ is the set of all possible treatment vectors. We encode the classical DID framework using a time treatment dummy $post_t$ that takes value one once the treatment is in place (when $t \geq k$, for some date k when the treatment starts) and zero before. In our application, we set $k = 2001$. We call a treatment allocation the time-varying indicator that takes value one when a member of the treatment group effectively receives the treatment (i.e. is observed after date k). We denote treatment allocation as $\mathbf{D}_t = \mathbf{D} \cdot post_t$. Because we allow for possible diffusion

[5] Our approach easily extends to data from repeated cross-sections.

effects of the policy to untreated units, we write the potential outcomes for unit i at date t as a function of the whole treatment allocation at date t: $Y_{i,t}(\mathbf{D}_t)$.[6]

The last crucial ingredient is a network accounting for the links between units. The network is summarized by a $N \times N$ proximity matrix A, where each term $a_{j,i}$ measures the strength of the relationship between i and j. For example, $a_{j,i}$ can take value one when unit i is connected to unit j. In our setting, $a_{j,i}$ takes value one when hydrographic zone j is upstream of hydrographic zone i. Figure 5a shows the A matrix for the French hydrographic zones, with dark pixels for when $a_{j,i} = 1$ and white pixels when $a_{j,i} = 0$. As the hydrographic network is a directed network, the A matrix is not symmetric. The hydrographic network is made of various arborescences. It is also possible to define the A matrix with $a_{j,i}$ being a continuous measure, e.g. the area of the watershed upstream of i that is covered by j.

Treatment exposure

The second part of the setting that is essential is the definition of treatment exposure. Here, again, we closely follow Manski (2013) and Aronow and Samii (2017), simply extending their concepts to a DID setting. We define the potential treatment exposure of unit i $\Delta_i = f(\mathbf{D}, \theta_i)$, where f is a mapping which goes from $\mathbf{\Omega} \times \mathbf{\Theta}$ in $\mathbf{\Delta}$. $\mathbf{\Theta}$ is a set of characteristics of each unit i, including the matrix A. $\mathbf{\Delta}$ is the set of treatment exposures. Potential treatment exposure measures the intensity with which unit i is affected by the treatment vector $\mathbf{D}$. Effective treatment exposure, which we define as $\tilde{\Delta}_{i,t} = \Delta_i \cdot post_t$, is the actual level of exposure to the treatment received by unit i. Because we are in a DID setting, effective treatment exposure is zero before the treatment date k. Since f is a mapping, treatment exposure can be characterized by a vector and not only by a scalar.

In our setting, we choose to define potential treatment exposure as the proportion of the area upstream of hydrographic zone i that is covered by the Nitrate Directive. We call this quantity treatment intensity and denote it as T_i. Formally, treatment intensity is defined as follows:

$$T_i = \frac{\sum_{j=1}^{N} a_{j,i} D_j}{\sum_{j=1}^{N} a_{j,i}}, \tag{1}$$

where $a_{j,i}$ is equal to the area of hydrographic zone j when it is upstream of i and zero otherwise. Figure 6 illustrates this definition. Hydrographic zone i has seven upstream hydrographic zones (including itself). Five of them, delimited by the dark square, belong to a vulnerable zone and are regulated under the Nitrate Directive. T_i is the sum of the area upstream of i that is regulated under the Directive (including i) divided by the total area upstream of i. T_i approximates the proportion of water streaming through i that has transited through areas affected by the Nitrate Directive.

[6]Note that our notation is already restrictive in that we do not allow for effects of the treatment at date t to have impacts at later dates. Extending our setting to allow for such effects is straightforward. In our application, since the treatment is fixed over most of the time periods, allowing for effects of the treatment to spill over time would not add much to the analysis.

Figure 6 also illustrates the bias that not accounting for diffusion effects generates for a treatment effect estimator and how the concept of treatment exposure corrects for this problem. Hydographic zones downstream of i are not classified as vulnerable and thus are not covered by the Nitrate Directive. But a large portion of the water flowing through these unregulated downstream hydrographic zones comes from rain that has fallen on regulated hydrographic zones. It is therefore highly likely that water quality in the hydrographic zones downstream of i has been affected by the regulation. A naive DID estimator not accounting for diffusion effects would classify these hydrographic zones as untreated and would include them in the control group, which would bias downwards the estimates of the impact of the regulation, since it would artificially decrease pollution levels in the control group. Our measure of treatment intensity accounts for the indirect exposure to the regulation of the hydrographic zones downstream of i. It thus avoids the biases of the classical DID estimator that assumes that diffusion effects are absent.

In practice, we choose to discretize our treatment intensity indicator T_i into several categories. This enables us to investigate potential non linear effects and to test for the existence of a dose-response relationship. Discrete treatment indicators allow us moreover to use the classical DID tools such as parallel trends graphs. We generate two discrete treatment indicators. The 25% threshold treatment indicator attributes to the treated group each hydrographic zone that has a treatment intensity higher than 25%. The 5-intensity treatment assigns each hydrographic zone into a treatment group corresponding to its treatment intensity from 0% to 100%, by 25% increments. Table 2 shows the assignment of hydrographic zones to each treatment group according to these two definitions. With the dichotomous treatment indicator, we end up with roughly half of the french hydrographic zones classified in the treatment group. With the 5-intensity treatment definition, we have around 3000 hydrographic zones in the control group, almost 500 hydrographic zones in the]25%,50%] treatment level, 261 in the]50%,75%] treatment level, roughly 1000 hydrographic zones in the]75%,100%[treatment level and 1250 hydrographic zones in the 100% treatment level.

Figure 7 shows the allocation of each hydrographic zone according to the two discretizations of treatment intensity. Two points are worthy of note. First, since the areas regulated under the Nitrate Directive exhibit a high degree of spatial correlation (see Figure 2) and are mostly located downstream of their main catchment areas, in practice there are very few unregulated hydrographic zones that are indirectly affected by the regulation. We should therefore not expect a strong downward bias from ignoring diffusion effects. Second, the fact that the main river streams appear in lighter colors than their surroundings on the map with detailed treatment intensity levels (Figure 7b) signals that their water quality depends on a larger watershed area. This clearly demonstrates that ignoring upstream influences would mask the impact of treatment intensity and thus might underestimate the steepness of the dose-response curve.

The key assumption of the setting delineated by Manski (2013) and Aronow and Samii (2017) is that treatment exposure summarizes exactly how each unit is affected by the treatment vector. It is formally encoded as follows:

Assumption 1 (Properly specified exposure mapping) $\forall i, t, \forall \mathbf{D}, \mathbf{D}' \in \mathbf{\Omega}$, $f(\mathbf{D}, \theta_i) = f(\mathbf{D}', \theta_i) \Rightarrow$

$Y_{i,t}(\mathbf{D}_t) = Y_{i,t}(\mathbf{D'}_t)$.

Under Assumption 1, we can write potential outcomes as a function of treatment exposure only: $Y_{i,t}(\mathbf{D}_t) = Y_{i,t}(\tilde{\Delta}_{i,t})$. Assumption 1 is a generalization of the assumption of absence of diffusion effects.[7] It restricts diffusion effects to have the shape embedded in the exposure mapping. In our application, Assumption 1 implies that the only way water quality in hydrographic zone i is affected by the Nitrate Directive is through treatment intensity $T_{i,t}$, that is the proportion of its upstream watershed that is under the regulation. In a first approximation, it makes sense that water quality downstream essentially depends on what happens upstream. Nevertheless, Assumption 1 coupled with our use of treatment intensity as a measure of treatment exposure is restrictive in a number of ways. First, we assume that the impact of the regulation moves downstream mechanically, and does not cross river streams (it does not go from one arborescence to another). We therefore exclude imitation effects, where farmers upstream or located in an unconnected hydrographic zone emulate the technical changes that the Directive imposes on farmers located in vulnerable zones. Second, we exclude market equilibrium effects, where changes in yields in regulated zones would affect the price of crops and change supply decisions outside of the regulated zones. In view of the limited production effects that we find at the farmer level, we are fairly confident that this issue is not of primary importance. Third, we exclude possible reallocation of manure from regulated areas to unregulated areas. We test for this assumption using data on manure transfers over space and find them to be very small. Fourth, we do not allow the impact of treatment to decay as we move up the river stream. It is nevertheless possible that the influence of what happens in hydrographic zone j matters less and less for water quality in i as j is further upstream from i. One way to capture this phenomenon would be to make the weights $a_{j,i}$ in the A matrix depend on the physical distance between i and j. We prefer to use a more non-parametric approach and test how our results are sensitive to the use of an alternative definition of treatment exposure that takes into account the distance between where treatment occurs and hydrographic zone i. We define the upstream distance $u(i,j)$ of zone j relative to zone i as the number of hydrographic zones between i and j, when j is upstream of i. For example, on Figure 6, the two hydrographic zones just upstream of i have $u(i,j) = 1$ and the two above are at a distance 2 relative to i. The distance between i and itself is zero, so that $u(i,i) = 0$. $u(.,.)$ is directional: the distance between i and its downstream zones is negative. We thus define a set of treatment intensities, one for each distance (or group of distances) as follows, for every distance $q \in \{1,\dots,Q\}$:

$$T_i^{u_q} = \frac{\sum_{j:u(i,j)=q} a_{j,i} D_j}{\sum_{j=1}^{N} a_{j,i}}. \tag{2}$$

$T_i^{u_q}$ measures the proportion of the upstream watershed of i that is regulated under the Nitrate Directive at distance q. $\left\{T_i^{u_q}\right\}_{q\in\{0,\dots,Q\}}$ is the set of treatment intensities at distances 0 to Q and one feasible alternative definition of treatment exposure.[8]

[7] SUTVA is indeed a special case of Assumption 1 where $f(\mathbf{D}, \theta_i) = D_i$.

[8] An alternative to formulating the shape of the treatment exposure mapping ex-ante would be to estimate the

Identification of the effect of treatment exposure in a DID setting

We are now equipped to define and study the identification of causal effects in a DID setting when there are diffusion effects. Let us first define our object of interest, the average effect of treatment exposure on the treated:

Definition 1 (Average effect of treatment exposure on the treated)

$$TT_t^Y(d) = \mathbb{E}[Y_{i,t}(\Delta_i) - Y_{i,t}(0)|\Delta_i = d].$$

Definition 1 shows that the treatment effect that we are interested in here is specific to a given level of exposure. There is therefore an infinite number of these effects, one for each level of treatment exposure. With our definition of treatment exposure as treatment intensity, d can theoretically take values in $[0, 1]$. In practice, we discretize treatment intensity into a dichotomous version and a polytomous five-level version. For the dichotomous version, there is only one average treament effect of treatment exposure. For the polytomous version, there are four different average effects of treatment exposure, one for each dose above the control dose. The polytomous version enables us to study whether there is a dose-response relationship between the regulation and water quality.

To obtain the identification of the average effect of treatment exposure using DID, we need to state additional assumptions, in addition to Assumption 1. We first need assumptions that will ensure that the expected potential outcomes at all levels of treatment exposure would have followed parallel trends in the absence of the treatment. We decompose this set of assumptions into four main assumptions. The first assumption is an additive separability assumption:

Assumption 2 (Additive separability) *Functions g, h and m and random variables μ_i, X_i, δ_t and $\epsilon_{i,t}$ exists such that:*

$$Y_{i,t}(\tilde{\Delta}_{i,t}) = g(\mu_i, X_i) + h(\delta_t, X_i) + m(\tilde{\Delta}_{i,t}, \mu_i, \delta_t, X_i) + \epsilon_{i,t}.$$

Assumption 2 requires that the effect of unobserved confounders on outcomes can be decomposed into four additively separable parts, one due to unobserved confounders fixed over time (or individual fixed effects) μ_i, one due to unobserved confounders that change over time but that do not change over space (or time fixed effects) δ_t, one where treatment exposure operates, possibly interacting with both time and unit fixed effects, and an idiosyncratic residual $\epsilon_{i,t}$. We allow each of the first three parts to interact freely with the level of the observed covariates X_i. An important question is whether there exists a plausible structural model of water quality along a river stream that would have such properties. We delineate one such model in Appendix A.1.

components of the A matrix from the data, using some form of machine learning estimator relating each observation i to the treatment in all the other zones j at every time period, as in Manresa (2016). Manresa's approach is not feasible in our case unfortunately, since we have very limited variation in the regulation over time and space. Another approach that we are keeping for further research would be to estimate a model of influence across outcomes, following for example Barigozzi and Brownlees (2019), and use the estimated weights to back out the weights applicable for the treatment.

The second assumption is an independence assumption:

Assumption 3 (Independence) $\mathbb{E}[\epsilon_{i,t}|\Delta_i, \mu_i, \delta_t, X_i] = 0$, $\forall t$.

Assumption 3 requires that the idiosyncratic innovations to the outcome process are independent from treatment exposure, conditional on the fixed effects and the observed covariates. Assumptions 2 and 3 allow the level of treatment exposure to be correlated with time and individual fixed effects. This means that areas that are the most polluted in general can receive a larger dose of the treatment. It was actually embedded in the design of the Nitrate Directive, where the definition of vulnerable zones implied that they encompassed areas with the largest levels of pollution. Assumptions 2 and 3 also allow pollution to decrease or increase for all areas in the same proportion in the absence of the Directive. Assumptions 2 and 3 are restrictive in that they prevent areas with different treatment exposure to undergo different trends over time. Assumption 2 requires that time and individual fixed effects do not interact, except for the effect of treatment exposure, which requires that time fixed effects have the same impact on all units (conditional on observables). Assumptions 3 requires that idiosyncratic innovations be independent from potential treatment exposure and have mean zero every year. Thus, idiosyncratic innovations cannot be correlated with treatment exposure.

The third assumption is a normalization:

Assumption 4 (Normalization) $\forall \mu, \delta, x,\ m(0, \mu, \delta, x) = 0$.

Assumption 4 requires that, when treatment exposure is zero, there is no interaction between individual and time fixed effects. Assumption 4 allows for unrestricted interactions between treatment exposure and individual and time fixed effects, which enables treatment exposure for example to have greater effects in certain places or at certain times.

Finally, we need a fourth assumption that ensures that there are units with a treatment exposure level of zero:

Assumption 5 (Existence of untreated units) $\Pr(\Delta_i = 0|X_i) > 0$.

Assumption 5 requires that there be a positive measure of units that receive zero exposure to the treatment. In our application, most units located at the most upstream parts of the French hydrographic network were not covered by the Nitrate Directive, which validates Assumption 5. As Lemma 1 in Appendix A.2 shows, Assumptions 1, 2, 3, 4 and 5 imply that the changes in outcomes in the absence of the treatment are identical at every level of treatment exposure (*i.e.* the Parallel Trends Assumption). We test for this assumption by comparing the trends at different exposure levels before the implementation of the Directive in 2001.

Let us finally define the DID estimator that we want to use to identify the effect of treatment exposure:

$$DID^Y_{k+\tau,k-\tau'}(d) = \mathbb{E}[\mathbb{E}[Y_{i,k+\tau} - Y_{i,k-\tau'}|X_i, \Delta_i = d] - \mathbb{E}[Y_{i,k+\tau} - Y_{i,k-\tau'}|X_i, \Delta_i = 0]|\Delta_i = d]. \quad (3)$$

Our DID estimator computes the average changes in outcomes between τ time periods after the treatment date and τ' time periods before the treatment date for the group of units with treatment exposure level d and compares it to the change between the same periods for the units with zero treatment exposure, conditional on observed covariates. It is thus a form of semi-parametric DID estimator (Heckman et al., 1997; Abadie, 2005). The following theorem shows that our DID estimator identifies the average effect of treatment exposure on the treated:

Theorem 1 (Identification of TT) *Under Assumptions 1, 2, 3, 4 and 5, the DID estimator identifies the average effect of treatment exposure on the treated:*

$$DID^Y_{k+\tau,k-\tau'}(d) = TT^Y_{k+\tau}(d).$$

Proof. See Section A.2. ■

Estimation and inference for the effect of treatment exposure with panel data

Theorem 1 opens the possibility for estimating the effects of treatment exposure on water quality using a DID-matching estimator. In practice, we prefer to resort to a simpler parametric model that enables us to use a rich set of fixed effects. We estimate the impact of the policy on the water quality indicator Y using the following regression:[9]

$$Y_{sirmt} = \sum_{l=1}^{L} \beta_l (T_i^l \times post_t) + \alpha' X_{sirmt} + \delta_s + \gamma_m + \theta_{rt} + \epsilon_{sirmt} \tag{4}$$

where Y_{isrmt} denotes water quality measured at station s, in hydrographic zone i, in hydrographic region r (there are five hydrographic regions in France), on month m of year t. T_i^l is a dummy variable taking value one when our treatment intensity indicator is at level l in the hydrographic zone i. L is the maximum number of treatment intensity levels, not including the control level. $L = 1$ for the *25% threshold* treatment and $L = 4$ for the *5-intensity* treatment. X_{sirmt} is a set of control variables including rainfall, temperatures, quality of measurement, measurement support, portion analyzed, and the reading is raw or has been controlled, analyzed or validated. We introduce a rich set of fixed effects: station fixed effects (δ_s), month-of-the-year fixed effects (γ_m) and region×year fixed effects (θ_{rt}). Station fixed effects account for the permanent shifters of pollution levels at the station level. Month-of-the-year fixed effects account for the cyclicality of pollution over the year, as it is particularly acute during the winter. Year fixed effects account for specific yearly pollution shocks common to all stations in the same region. We choose to make these yearly fixed effects specific to each hydrographic region, to account for possible region-specific trends in pollution. Our analysis thus looks at how pollution changes after 2001 at stations exposed to the regulation, comapred to what happens to stations located in the same region but not exposed to the regulation.

[9] The structural model of water quality along a river stream that we present in Appendix A.1 is compatible with the parametric model we use for estimation.

We compare our modified DID estimator to a classical DID estimator that ignores diffusion effects. We write the classical DID estimator as follows:

$$Y_{sirmt} = \sum_{l=1}^{L} \beta_l^c (D_i^l \times post_t) + \alpha^{c'} X_{sirmt} + \delta_s^c + \gamma_m^c + \theta_{rt}^c + \epsilon_{sirmt}^c, \tag{5}$$

where D_i^l is a treatment intensity variable defined by the proportion of the area of hydrographic zone i that is covered by the regulation, ignoring what happens upstream of i. We also estimate a version of the geographical discontinuity design estimator of Keiser and Shapiro (2017):

$$Y_{sipzrmt} = \beta^{ks} (D_p \times post_t \times down_z) + \alpha^{ks'} X_{sirmt} + \delta_s^{ks} + \gamma_m^{ks} + \phi_{zt}^{ks} + \theta_{zrt}^{ks} + \epsilon_{sipzrmt}^{ks} \tag{6}$$

This estimator is computed only on pairs p of contiguous hydrographic zones i located around the borders of the vulnerable zones. The position of each hydrographic zone i in each pair p is encoded by the index z, which takes value one if the hydrographic zone is downstream in the pair and zero if it is upstream. The variable $down_z$ takes value one when $z = 1$. The treatment variable, D_p, takes value one if the downstream hydrographic zone in the pair is covered by a vulnerable zone and zero otherwise. Keiser and Shapiro (2017) introduce pair×downstream fixed effects, which would be equivalent in our case to hydrographic zones fixed effects. We prefer to use more fine-grained station specific fixed effects δ_s^{ks}. Two additional sets of fixed effects are key to the identification strategy in Keiser and Shapiro (2017): pair×year fixed effects (ϕ_{pt}^{ks}) that account very finely for time trends specific to each pair and enable the estimation to focus only on changes in pollution within each pair; and downstream×region×year fixed effects, θ_{zrt}^{ks}, which account for differential trends between upstream and downstream hydrographic zones in each region, capturing the effect of other sources of pollution that would systematically be located within vulnerable zones. Keiser and Shapiro (2017)'s approach does not allow the effect of the regulation to accumulate along the river stream. It is thus likely that this estimator is biased downwards.

One final important question is how to estimate the precision of our estimators of the effect of the Nitrate Directive accounting for the very likely autocorrelation between error terms along river streams and over time. We first follow Barrios et al. (2012) and estimate the extent of autocorrelation in our data empirically to guide our choice of the best estimator for precision. We especially focus on the extent of autocorrelation along river streams by estimating the empirical covariance $\hat{C}(q)$ at each distance q:

$$\hat{C}(q) = \frac{\sum_{i=1}^{N} \sum_{j:u(i,j)=q} Y_i Y_j}{\sum_{i=1}^{N} \sum_{j:u(i,j)=q} \mathbb{1}[j : u(i,j) = q \geq 0]}, \tag{7}$$

where $\mathbb{1}[A \geq 0]$ takes value one when A is true and zero otherwise. We also cluster our estimates either at the station level or at the hydrographic zone level. The latter approach accounts for both temporal autocorrelation and for spatial autocorrelation among stations that belong to the same hydrographic zone. Finally, we extend to the DID setting Leung (2020)'s estimator for the covariance matrix of a linear regression on a network based on cross-sectional data (and predated on the analysis of a Randomized Controlled Trial conducted on a network). The extension is pretty straightforward, in that in Leung (2020)'s formula we replace the covariates in levels by the demeaned covariates $\tilde{X}_i$. We thus use the following estimator for the covariance matrix $\hat{\Sigma}$ of the parameters of equation (4) estimated using a fixed effects estimator:

$$\hat{\Sigma} = (\tilde{X}'\tilde{X})^{-1}\mathcal{M}'G\mathcal{M}(\tilde{X}'\tilde{X})^{-1}, \tag{8}$$

where $\tilde{X}$ is the matrix of demeaned covariates, $\mathcal{M}$ is a matrix where columns are the product between each demeaned covariate and $\hat{\epsilon}_{isrmt}$ the estimated residuals from equation (4), and G is a matrix accounting for the autocorrelation between observations. Figure 5b shows the G matrix for the cross-section of hydrograghic zones that is the symmetric matrix built from A. It accounts for potential autocorrelation between all observations that belong to the same river stream by connecting all the observations that are in an upstream/downstream relationship. In practice, the G matrix that we use is much larger (it has the same number of lines as there are observations in our panel dataset). The G matrix that we use accounts for spatial correlation over space (using the pattern encoded in Figure 5b) but also accounts for autocorrelation over time by connecting observations from the same station and/or the same hydrographic zone in different time periods.

Randomization inference tests for the existence and shape of diffusion effects

We complement our approach by randomization inference tests, extending tools developed for the analysis of Randomized Controlled Trials conducted on a network by Athey et al. (2018). The way we extend their approach is to apply the tests not directly on the outcomes in levels, but on the demeaned outcomes $\tilde{y}_{sirmt}$, obtained as the residuals of a regression of the outcomes in levels on the fixed effects, without the treatment variables. Under our assumptions, these residuals should be as good as random with respect to the treatment.

We perform several randomization inference tests. We first test whether there are any effects of the treatment. The null hypothesis in this case is that all the effects of the treatment are zero: $Y_{i,t}(\mathbf{D}_t) = Y_{i,t}(\mathbf{D'}_t)$, $\forall i, \forall \mathbf{D}, \mathbf{D'} \in \mathbf{\Omega}$. To test for this assumption, we randomly allocate all hydrographic zones to placebo vulnerable zones, which gives us a randomized treatment vector $\tilde{D}_i$. To test for the existence of a treatment effect, we use as test statistics $\hat{\beta}_{OLS}$ and $\hat{\delta}_{DID}$, estimated using the following regressions:

$$\tilde{y}_{sirmt} = \alpha_{OLS} + \beta_{OLS}\tilde{D}_i + \eta^{OLS}_{sirmt},\ t \geq 2001 \tag{9}$$

$$\tilde{y}_{sirmt} = \alpha_{DID} + \beta_{DID}\tilde{D}_i + \gamma_{DID}post_t + \delta_{DID}\tilde{D}_i post_t + \eta^{DID}_{sirmt}. \tag{10}$$

We compare the estimates of $\hat{\beta}_{OLS}$ and $\hat{\delta}_{DID}$ obtained using the true treatment allocation to the distribution obtained by randomly allocating the treatment status across hydrographic zones.

We also test for the existence of diffusion effects. The null hypothesis in this case is that all diffusion effects beyond some distance q are non-existent: $Y_{i,t}(\mathbf{D}_t) = Y_{i,t}(\mathbf{D'}_t)$, $\forall i, \forall \mathbf{D}, \mathbf{D'} \in \mathbf{\Omega}$ such that $D_j = D'_j$ $\forall j$ such that $u(i,j) \geq q$. This is crucial because implicit in our formulation of treatment exposure is the fact that when regulating a hydrographic zone, we affect water quality not only there but also in the zones located downstream. In practice, we test for the existence of effects of order one and two, that is for $q = 1$ and $q = 2$ in the hypothesis above. We implement the tests proposed by Athey et al. (2018) as follows. We first select a set of focal units. In our case, these units are the ones for which we observe water quality at some point in time. To test for effects of order one, we first select all the hydrographic zones that are one upstream hydrographic zone away from the focal ones. Athey et al. (2018) call these units the auxiliary units. We randomly allocate the treatment among the auxiliary units, obtaining a random treatment vector among auxiliary units $\tilde{D}_i^1$. To test for the null hypothesis, we use as test statistics $\hat{\gamma}_{OLS}$ and $\hat{\rho}_{DID}$, estimated using the following regressions:

$$\tilde{y}_{sirmt} = \alpha_{OLS} + \beta_{OLS} D_i + \gamma_{OLS} \tilde{D}_i^1 + \eta_{sirmt}^{OLS},\ t \geq 2001 \tag{11}$$

$$\tilde{y}_{sirmt} = \alpha_{DID} + \beta_{DID} D_i + \phi_{DID} \tilde{D}_i^1 + \gamma_{DID} post_t + \delta_{DID} D_i post_t + \rho_{DID} \tilde{D}_i^1 post_t + \eta_{sirmt}^{DID}. \tag{12}$$

To test for diffusion effects of order two, we select as auxiliary units the hydrographic zones that are two upstream hydrographic zones away from the focal ones and we randomly allocate the treatment among them ($\tilde{D}_s^2$). To test for the null hypothesis, we use as test statistics $\hat{\delta}_{OLS}$ and $\hat{\theta}_{DID}$, obtained estimating the following regressions on the focal units:

$$\tilde{y}_{sirmt} = \alpha_{OLS} + \beta_{OLS} D_i + \gamma_{OLS} D_i^1 + \delta_{OLS} \tilde{D}_i^2 + \eta_{sirmt}^{OLS},\ t \geq 2001 \tag{13}$$

$$\begin{aligned} \tilde{y}_{irmt} = {} & \alpha_{DID} + \beta_{DID} D_i + \phi_{DID} D_i^1 + \psi_{DID} \tilde{D}_i^2 + \gamma_{DID} post_t \\ & + \delta_{DID} D_i post_t + \rho_{DID} D_i^1 post_t + \theta_{DID} \tilde{D}_i^2 post_t + \eta_{sirmt}^{DID}. \end{aligned} \tag{14}$$

We also test for the existence of a dose-response relationship. The null hypothesis in that case is that there are no effects when treatment intensity moves beyond 0.25: $Y_{i,t}(\mathbf{D}_t) = Y_{i,t}(\mathbf{D'}_t)$, $\forall i, \forall \mathbf{D}, \mathbf{D'} \in \mathbf{\Omega}$ such that $\mathbb{1}[\Delta_i \geq 0.25] = \mathbb{1}[\Delta'_i \geq 0.25]$. To test for this hypothesis, we select as focal units all the most downstream units. We then move upstream until the cumulative area regulated under the directive reaches 25% of the total area of the upstream watershed of each focal unit. We classify as auxiliary units all the units that are located beyond the 25% threshold. We randomly allocate the treatment among the auxiliary units and obtain a cumulated treatment intensity among auxiliary units $\tilde{T}_i$. To test for the null hypothesis, we use as test statistics $\hat{\beta}_{OLS}^T$ and $\hat{\delta}_{DID}^T$, obtained by estimating the following regressions on the focal units:

$$\tilde{y}_{sirmt} = \alpha_{OLS} + \beta_{OLS}^T \tilde{T}_i + \eta_{sirmt}^{OLS},\ t \geq 2001 \tag{15}$$

$$\tilde{y}_{irmt} = \alpha_{DID} + \beta_{DID} \tilde{T}_i + \gamma_{DID} post_t + \delta_{DID}^T \tilde{T}_i post_t + \eta_{sirmt}^{DID}. \tag{16}$$

Finally, we account for clustering in the implementation of the Directive by randomly allocating the treatment among clusters of three hydrographic zones. We build these clusters by moving upstream along each river stream from its most downstream point, allocating to the same cluster all the hydrographic zones that are less than two zones away from the focal one, and repeating the operation until we reach the most upstream hydrographic zone in each arborescence.

Extensions to other applications

Our methodological extension of the DID estimator to interventions that have spillover effects on a network can be of separate interest for other applications for which Randomized Controlled Trials might not be feasible, but where a source of spatial and temporal variation in treatment exposure exists. Diffusion or spillover effects affect multiple economic, social, and biological phenomena such as water and air pollution, traffic congestion, the transmission of contagious diseases and the diffusion of innovations, among many others. The proximity matrix A might be the most crucial component when applying the approach delineated here to other situations. In applications where interactions are mechanistic, because for example they stem from biophysical processes, such as the diffusion of pollution along river streams or wind directions, the proximity matrix can easily be defined by the observed physical flows. For example, for applications to air quality, one could define the A matrix as the proportion of the time the wind from location i flows in the direction of j, or reaches location j.

In other applications, especially characterized by behavioral interactions (such as migration or traffic congestion, for example), building the A matrix might require more work. Take the example of a workfare program that might have effects on labor markets and, as a consequence, on untreated units, as for example in Imbert and Papp (2020). One way to define the A matrix in that case is to say that individuals are connected if they share the same labor market (and possibly the same type of task or job). This might be restrictive, though, since new migration might occur in the zones to which workers taking up the workfare program used to migrate. If the strength of these migrations differs among zones, then treatment exposure should reflect that variation. Estimating a model of how migration flows as in Imbert and Papp (2020) might help build the exposure matrix. In the case of a policy prohibiting traffic in certain areas on high pollution days, building the A matrix is even more difficult. Simply using observed flows does not allow to predict how flows will react to the policy. Using a model of transport and route choice accounting for the fact that some routes are inaccessible might help to build the A matrix. Our approach can then serve as a test for the predictions of the structural model.

4.2 Estimating the effect of the Nitrate Directive on farmers

At the farmer level, we have access to two types of datasets: a repeated cross-section (the survey of agricultural practices) and a rotating panel (the Farm Accountancy Data Network). With the repeated cross-section, we use a traditional DID approach:

$$Y_{pt} = \beta(Vulnerable_p \times post_t) + \gamma Vulnerable_p + \phi_{d(p)} + \psi_t + \epsilon_{pt}, \quad (17)$$

where Y_{dt} is an agricultural practice of interest on plot p in year t and in department $d(p)$. $Vulnerable_p$ is a dichotomous variable that takes value one when plot p is regulated under the Nitrate Directive and zero otherwise. $\gamma Vulnerable_p$ captures the average level of the agricultural practice for the group of plots regulated under the Nitrate Directive before the regulation is implemented. $\phi_{d(p)}$ and ψ_t are *département* and year fixed effects respectively.[10]

With the rotating panel data of the Farm Accountancy Data Network, we run a more classical panel data regression:

$$Y_{ft} = \beta(Vulnerable_f \times post_t) + \chi_f + \zeta_t + \epsilon_{ft}, \tag{18}$$

where Y_{ft} is an agricultural practice of interest on farm f in year t. $Vulnerable_f$ is a dichotomous variable that takes value one when farm f is located in a commune regulated under the Nitrate Directive and zero otherwise. χ_f and ζ_t are farm and year fixed effects respectively.

5 Results

This section presents our main results. The first part presents the impacts of the EU Nitrate Directive on water quality, while the second part details the impacts of the Directive on farmers' practices and profits. A third part provides the most relevant robustness checks, including the results of using alternative estimators, alternative methods for estimating precision, and randomization inference tests.

5.1 Impacts of the Nitrate Directive on water quality

We first present the impacts of the Nitrate DIrective on nitrate concentration. We then move on to results on other physico-chemical indicators of water quality before ending with results on eutrophication and biodiversity.

Impacts on nitrate concentration

In this section, we first show descriptive evidence of the impact of the Nitrate Directive on nitrate concentrations in water before presenting results obtained estimating equation (4).

Figure 8a shows the annual mean nitrate concentration in surface waters at each level of treatment intensity. Several findings are apparent on this graph. First, hydrographic zones with higher levels of treatment intensity have higher levels of nitrate concentration before 2001. This makes sense since vulnerable areas were selected because they had high levels of nitrate pollution before 1993. Second, before 2001 the trends in nitrate concentration are roughly similar (and actually rather flat) in areas with different levels of treatment intensity, thus vindicating the assumption of parallel trends that underlies the DID approach that we use. Third, water quality improves in the group with the highest treatment intensity, whereas it remains constant in control areas, thereby

[10] The *département* is the second smallest administrative level in France. There are roughly 100 *départements* containing on average 360 communes each.

suggesting that the Nitrate Directive improves water quality, at least when enough of the upstream watershed is regulated under the Directive. Figure 8b shows the trends in water quality in treated groups compared to the control group. The trends in water quality in treated watersheds do not exhibit major upward or downward trends before 2001. The mean level of water quality compared to the control group (in red) decreases after 2001, and seems to decrease more at higher treatment intensity.

Figure 9 reports estimates of the impact of the Nitrate Directive on nitrate concentration in surface water obtained using Equation (4) and the two treatment definitions (2-levels on the left and 5-levels on the right). Table 3 presents the actual magnitudes of the estimates. There are two important results from Figure 9. First, when grouping all treatment intensities above 25% together, we estimate that the Nitrate Directive reduces nitrate concentration in surface water by 1.23±0.27 mg/l, a decrease of roughly 8% with respect to a mean concentration level of 16 mg/l. Second, the impact of the Nitrate Directive on water quality exhibits a dose-response relationship: nitrate concentration decreases as the share of the upstream watershed regulated under the Directive increases. The reduction in nitrate concentration that we measure goes from 0.05±0.30 mg/l when 25% to 50% of the upstream watershed is regulated under the Directive, to 0.73±0.41 mg/l when 50% to 75% of the upstream watershed is regulated, 1.37±0.43 mg/l when 75% to 99% of the upstream area is regulated, finally reaching 2.82±0.44 mg/l when 100% of the upstream watershed is regulated under the Directive.

Table 4 displays the results of a heterogeneous analysis of the effect of the Nitrate Directive by season and by region. We find the most important effects of the Directive to be concentrated during winter, when nitrates are at a higher risk of running off from the fields. We also find that the impact of the Directive is greatest in the Loire-Bretagne hydrographic district, with a reduction in nitrate concentration of 3.90±0.72 mg/l, followed by the Seine-Normandie hydrographic district, with a reduction in nitrate concentration of 1.18±0.80 mg/l. The large impact in Loire-Bretagne is probably due to the fact that a large portion of the area there is regulated under the Directive.

Impacts on other physico-chemical indicators of water quality

Figure 10 presents the mean concentrations in treated and control groups and the deviations from the control group for the concentrations in nitrites, ammonium and phosphorus and for dissolved oxygen and chemical oxygen demand. When looking at the plots on the left, it seems that the water concentrations in nitrites, ammonium, phosphorus and chemical oxygen demand decrease more in treated areas than in control areas before 2001, suggesting a potential failure of the Parallel Trends Assumption underlying DID. This might be because the first action program starting in 1997 actually reduced pollution, contrary to our assumptions so far. Note that if this is the case, our estimates underestimate the reduction of pollution due to the EU Nitrate Directive. But these trends might also be due to confounding influences, for example the differences in temporal trends in water pollution between hydrographic regions before 2001. This second explanation seems vindicated when looking at the plots on the right: adding region×year fixed effects gets rid of the diverging trends. Comparisons of pre- and post- 2001 levels of pollution in the treated group with respect to the control group (in red on the plots on the left) suggests that the Nitrate Directive has improved water quality.

Table 5 presents econometric estimates of the impact of the Nitrate Directive on the concentrations of nitrites, ammonium and phosphorus, dissolved oxygen and chemical oxygen demand obtained by estimating equation (4). The econometric results confirm the visual impression obtained after looking at Figure 10. We find that the Nitrate Directive decreases concentrations in nitrites by 0.032 ± 0.012 mg/l, in ammonium by 0.12 ± 0.11 mg/l and in phosphorus by 0.027 ± 0.022 μg/l. We also find that the Nitrate Directive increases the concentration in dissolved oxygen by 0.06 ± 0.07 mg/l. We find very imprecise results with respect to the impact of the Directive on chemical oxygen demand, where we find an imprecisely estimated increase of 0.19 ± 1.01 mg/l. Results estimated with our balanced sample find a decrease in chemical oxygen demand of 1.56 ± 1.7, which is still very imprecise (see Table 14). These changes correspond to roughly a 10% improvement relative to their mean, except for ammonium, where the change represents roughly 5% of its average concentration, and dissolved oxygen, where the change in concentration is of the order of 1‰.

Impacts on eutrophication and biodiversity

Figure 11 presents the trends in the concentration in Chlorophyll A, the number of fish and the number of fish species in treated and control watersheds. Figures 11a, 11c and 11e show that the concentration in Chlorophyll A, the number of fish and the number of fish species seem to improve more in treated areas than in control areas before 2001. This might be due either to improvements owing to the first action program that started in 1997, or to diverging trends, possibly at the hydrographic region level. Introducing region$\times$year fixed effects transforms the diverging trends in an oscillation compatible with the parallel trends assumption (Figures 11b, **??** and 11f). These figures also show that water quality improves in the treated areas compared to the control areas after 2001. Table 6 shows the results of regressions estimating equation (4) for the concentration in Chlorophyll A, the number of fish and the number of fish species. We find that the Nitrate Directive reduces the concentration in Chlorophyll A by 2.7 ± 1.4 μg/l, a decrease of more than 20% relative to the baseline level. We also find that the stock of fish increases by 70 ± 22, an increase of 40% relative to the average fish population at our measurement points. The number of fish species increases by almost one (0.92 ± 0.44), or roughly 10% of its baseline level.

5.2 Impacts on farmers' practices and productivity

In this section, we present the impacts of the Nitrate Directive on farmers' practices, profits and productivity. We present the impacts of the Directive on practices aimed at reducing the transfers of pollutants in a first part, on nitrogen use efficiency in a second part and on farmers' profits and productivity in a last part.

Impacts on practices aimed at reducing the transfer of pollutants

Figure 12 presents the trends in adoption of nitrate-fixing crops and grass buffer strips by farmers located inside and outside the vulnerable zones delimited by the Nitrate Directive. Figure 12a shows that, before 2001, the adoption of nitrate-fixing crops was increasing slowly in both types of zones. After 2001, farmers started planting nitrate-fixing crops at a much higher rate in zones regulated under the Nitrate Directive. Figure 12c shows that the adoption of grass buffer strips skyrocketed after 2001, but that the rate of increase was similar both in vulnerable and in non-vulnerable zones. This suggests that the Nitrate Directive succeeded in increasing the adoption of nitrate-fixing crops, but failed at increasing the planting of grass buffer strips, which increased for other reasons. Since 2001, subsidies from the first pillar of the Common Agricultural Policy have been conditional on the planting of grass buffer strips, which triggered a general increase of these strips in vulnerable and non-vulnerable zones alike.

Table 7 confirms this analysis by showing estimates of equation (17). Our estimates show that the Nitrate Directive increased the adoption of nitrate fixing crops by 6$\pm$1 p.p., a more than 100% increase relative to the mean, while the Nitrate Directive did not affect the proportion of farmers planting grass buffer strips (-1.0$\pm$2.4 p.p.).

Impacts on practices aimied at increasing the effectiveness of nitrogen management

Figure 13 shows the evolution of the proportion of farmers estimating nitrogen content in the soil and adjusting their nitrogen fertilization using the nitrogen balance method in zones covered or not covered by the Nitrate Directive. Both practices serve to adapt the amount of nitrogen fertilizer applied to the field to the needs of the plant and the nitrogen content in the ground. Figure 13b shows that the proportion of farmers performing soil analysis to measure the Nitrogen content by the end of winter increases over time more in zones covered by the Nitrate Directive than in zones not covered by it. Similarly, and even more strikingly, Figure 13c shows that the proportion of farmers adjusting their nitrogen input using the nitrogen balance method has increased by roughly 10 p.p. in zones covered by the Nitrate Directive relative to zones not covered by it.

Table 8 confirms the impression taken from Figure 13 with estimates of equation (17). It shows that the Nitrate Directive increased the proportion of farmers estimating the level of nitrates in their field by 6.4$\pm$2.8 p.p and the proportion of farmers adjusting their nitrogen input using the nitrogen balance method by 10.2$\pm$2.0 p.p., which correspond to increases of 50% and 71% respectively with respect to the mean.

Impacts on nitrogen use and nitrogen use efficiency

Figure 14 presents the evolution of fertilizer use for plots of land regulated or not under the Nitrate Directive. We do not see clear changes in mineral fertilizer use, but can observe a signs of a decrease in manure use after 2001. Figure 15 presents the evolution of nitrogen input, output, balance, and nitrogen use efficiency for plots of land regulated or not under the Nitrate Directive. While we do not observe clear changes in nitrogen input on plots regulated under the Nitrate Directive, there is a differential increase in nitrogen output on those plots, which translates into a relative increase in nitrogen use efficiency and a decrease in nitrogen balance.

Table 9 confirms the results of the visual inspection of Figure 14 and Figure 15 by providing estimates of equation (17). We find statistically insignificant effects of the Nitrate Directive on mineral fertilization (both for nitrogen (-2.8±3.4 kgN/ha) and phosphorus (-1.5±2.1 kgP/ha)), while we find small but significant effects of the Nitrate Directive on manure use (-1.4±1.2 kgN/ha). Hence, we find no impact of the Nitrate Directive on the total amount of nitrogen input brought to the field (0.88±4.6 kgN/ha). As expected from what we saw on Figure 15, we find that the Nitrate Directive increases the output content in nitrogen by 9.6±4.8 kgN/ha, relative to a mean of 136.1, which is an increase of 7%. This has led to an improvement in nitrogen use efficiency by 16±7 p.p., and a decrease in nitrogen balance by 9.6±6.6 kgN/ha.

Impacts on farmers' profits and productivity

Table 10 presents the results of estimating equation (18) for the components of farmers' per-hectare profits on the FADN data, using the farmer's location in a vulnerable zone or not as the treatment indicator. We first confirm the results obtained using plot-level data, *i.e.* the total value of production increases in vulnerable areas. We quantify this increase as equal to 18±12 €/ha for all the farmers regulated under the Directive. This increase in the value of output is larger for crop growers, who get to benefit the most from increases in crop yields. The value of their output increases by 29±24 €/ha thanks to the Directive. This amounts to a 2% increase in the value of the production of a typical crop grower over this period. When subtracting their spending on fertilizers from the total value of production, we still find that the Directive improves farmers' gross profits (by 13±12 €/ha for all farmers and by 23±24 €/ha for crop growers). When subtracting the costs of all the other main variable inputs (seeds, pesticides, fuel, and soil analysis), we find that the Directive has an insignificant effect on farmers' gross profits (6±12 €/ha for all farmers and 13±24 €/ha for crop growers). Hence, we find that the Directive has not negatively impacted farmers' gross profits.

To examine the overall impact of the Directive on farmers' economic performance, we estimate its impact on total factor productivity. Table 11 reports on the results of estimating equation (18) with total factor productivity as an outcome, with various levels of fixed effects. The results of these regressions show that the Nitrate Directive increases farmers' total factor productivity by 0.05±0.04, an 8% increase relative to the mean total factor productivity in the sample. The Nitrate Directive seems to have increased the productivity of the regulated farmers, a result consistent with the Porter hypothesis (Porter and Van der Linde, 1995). The Porter hypothesis states that regulations might trigger the adoption of innovations by the regulated firms in order to cope with the additional costs of the regulation.

A key question in the literature on the Porter hypothesis is how a regulation can improve the productivity of the regulated firms. In our case, we think we have a fairly clear explanation for why the Nitrate Directive might have increased farmers' total factor productivity: the mandatory adoption of improved nitrogen management methods, especially soil analysis coupled with the nitrogen balance method. Our interpretation of our results is that these technologies improve the allocation of nitrogen by bringing it to where it is most needed. This increases the amount of nitrogen exported in the crops and decreases the amount of nitrogen running off from the fields, thereby increasing nitrogen use efficiency. One way to test for this explanation is to examine whether the variance of the quantities of nitrogen fertilizers brought to the fields increases in the zones covered by the Nitrate Directive. If farmers adapt the quantity of fertilizer used, by applying more where it is needed most, and less where more nitrogen remains after winter, based on the results of soil analysis and the nitrogen balance method, then the quantities applied to each field should vary more since they are tailored better to the specific needs of each field. Table 12 shows that the variance in the application of nitrogen fertilizer increases in vulnerable areas after the implementation of the Nitrate Directive, as we would expect if the applications had become more sensitive to the specific conditions in each field, specifically the content of nitrogen after winter.

5.3 Robustness Checks

In this section, we present the results of several robustness checks. First, we discuss the conditions of selection of the hydrographic zones in vulnerable areas in relation to the parallel trends assumption. Second, we test how our estimates change when using alternative estimators. Third, we report on how our estimates of precision change when accounting for autocorrelation along river streams. Fourth, we present evidence on the existence of diffusion effects and on the validity of our assumed exposure mapping. Fifth, we test how our results vary depending on the sample of monitoring stations we use and on the type of fixed effects. Sixth, we look at how our results change when we control for land use changes. Seventh, we test the sensitivity of our results to the inclusion of controls for the installation of wastewater treatment plants along river streams.

Delimitation of the vulnerable zones and validity of the parallel trends assumption

A key assumption for the validity of our approach is the parallel trends assumption which states that, in the absence of the treatment, trends in water quality are independent of treatment exposure. Figure 8b suggests that the pre-2001 trends in Nitrate concentration hovers around zero in all groups of treatment intensity, but we have not yet provided a formal test for this assumption. In this section, we want to provide more evidence to support that assumption, and how it follows from the process of selection of hydrographic zones into vulnerable zones.

Let us start by discussing the conditions under which the official rules used to delimit the vulnerable zones are compatible with the parallel trends assumption. We do not know the exact rules of selection of vulnerable zones, but we know the general guidelines: stations and zones that had maximum nitrate concentrations above 40 or 50 mg/l in the years before 1993 should be included in a vulnerable zone. Figure 16 shows that the maximum concentration in nitrates observed before 1993 is strongly correlated with the proportion of the area of a hydrographic zone classified as vulnerable to nitrate pollution. The proportion of vulnerable zones increases with maximum concentration up to 50 mg/l, and then levels off, except in 1993 where it keeps increasing even above 50 mg/l, suggesting that readings made in 1993 are the ones that regulators used to define the boundaries of the vulnerable zones. We can thus model the selection of the vulnerable zones as a threshold crossing model: $D_i = \mathbb{1}[Y_{i,1993} + \eta_i \geq 50]$, where η_i is a mean zero shock.[11] Following Chabé-Ferret (2015), we model nitrate concentrations in the absence of the treatment in hydrographic zone i in year t as an AR(1) process with zone specific intercepts and trends: $Y^0_{i,t} = \mu_i + \beta_i t + U_{i,t}$, with $U_{i,t} = \rho U_{i,t-1} + \epsilon_{i,t}$, and $\epsilon_{i,t}$ an i.i.d. mean-zero shock.[12] Combining the two equations (and as shown formally in Chabé-Ferret (2015)), the difference between nitrate concentrations in vulnerable zones and non-vulnerable zones will start increasing as we get closer to 1993, because of the increasing influence of β_i and $U_{i,t}$, which are both positively correlated with selection into a vulnerable zone, and increasingly so as we get closer to 1993. Our simple model of selection thus predicts that the parallel trends assumption will not hold before 1993, unless the variance of β_i is zero and $\rho = 0$ (see Chabé-Ferret (2017) for a formal proof). The model also predicts that the difference between treated and control groups will continue to grow after 1993 if the β_i term dominates. If the variance of β_i is zero and $|\rho| < 1$, the difference between treatment and control groups will start shrinking after 1993. Finally, if the variance of β_i is zero and $\rho = 1$, the difference between treated and control groups will remain constant after 1993, ensuring the validity of the parallel trends assumption.

Because selection into vulnerable zones was done in 1993, and the regulations of the Nitrate Directive did not take effect before 2001, we have six years (between 1994 and 2000) during which we can test which of the three cases of selection bias dynamics described above actually holds. Figure 17 shows the trends in nitrate concentrations in each of the $5 - intensity$ treatment groups before 1993, between 1994 and 2000 and after 2001. As expected, we see that there is an increasing divergence in nitrate concentrations between the treated groups and the control group up to 1993. The steepness of this divergence increases with treatment intensity, as we could expect, since higher treatment intensity means a bigger share of the watershed located upstream of the hydrographic zone covered by vulnerable zones. After 1993, the divergence of nitrate concentrations between the treated and control groups levels off and remains constant, as predicted by a model where the variance of β_i is zero and $\rho = 1$. A formal test does not reject the null hypothesis that the trends in nitrate concentrations in each treatment groups are significantly different from the trends in the control group between 1994 and 2000.[13]

[11] Note that this selection equation opens up the possibility of using a Regression Discontinuity Design with the maximum nitrate concentrations registered in 1993 as a running variable. Weindeed find a very sharp increase in the proportion of vulnerable area around 39.5 mg/l of maximum concentration of nitrates in 1993, and a corresponding sharp decline of mean nitrate concentrations around the same threshold after 1997. However, the estimates rely on a handful of observations and are thus highly imprecise. We therefore do not report them here.

[12] For simplicity, we ignore spatial autocorrelation, which does not alter the analysis.

[13] We perform the test by estimating the slope of a linear regression relating treatment group×year dummies, estimated using equation (4) modified to replace $post_t$ by a set of yearly dummies, with time, separately for each treatment group, using Weighted Least Squares, with the weights the inverse of the square of the standard error of the estimated parameters. The estimated slopes are 0.032 ± 0.422 for group 1, 0.155 ± 0.57 for group 2, $0.412 \pm$

We can therefore rule out both the model in which the variance of β_i is zero and $|\rho| < 1$ and there is regression to the mean and the model in which the variance of β_i is positive and the divergence between treatment and control groups increases over time. The model that is compatible with our data is one in which the variance of β_i is zero and $\rho = 1$, and the parallel trends assumption holds after the date of selection of the vulnerable zones. In this model, shocks to nitrate concentrations are permanent. This makes intuitive sense: the stock of cattle and the area dedicated to crops are both highly persistent over time. Our reading of this evidence is that the parallel trends assumption is verified in our data after 1993, and thus our main identification assumption holds.

Alternative estimators

Table 13 presents the results of estimating the impact of the Nitrate Directive on nitrate concentrations using alternative methods: the classical DID approach ignoring diffusion effects, as delineated in equation (5) and the geographical discontinuity design estimator of Keiser and Shapiro (2017) presented in equation (6).

The results show that the classical DID estimator ignoring diffusion effects finds a reduction of 1.14$\pm$0.24 mg/l in nitrate concentrations because of the treatment when it is defined as a dichotomous treatment, *vs* 1.23$\pm$0.27 mg/l for our modified estimator. We were expecting the bias due to diffusion effects to be small, since the zones covered by the Nitrate Directive are spatially correlated and mostly located downstream of the hydrographic network, leaving few zones that are not covered by the Directive but that benefit from its impact. In contrast, we find that the classical DID estimator would miss the steepness of the dose-response relationship, as columns (4) and (5) of Table 13 show. Coefficients for the doses of treatment intensity equal to $[0.5, 0.75[$, $[0.75, 1[$ and 1 are underestimated by a factor of 1.4 to 4. As a consequence, the true effectiveness of cumulating the effect of the policy along river streams would have been downplayed by the classical DID estimator.

Table 13 also presents the results of the geographical discontinuity design estimator of Keiser and Shapiro (2017) detailed in equation (6). This estimator finds a statistically significant decrease in nitrate concentrations due to the reform of 1.07$\pm$0.64 mg/l. This is slightly smaller and less precise than the effect we find with our estimator (1.23$\pm$0.27 mg/l), but still in the same range. Figure 18 presents the trends in nitrate concentrations obtained using Keiser and Shapiro (2017)'s method. The difference between neighboring vulnerable and non-vulnerable zones hovers around zero before 2001, confirming the validity of the assumption of parallel trends on which Keiser and Shapiro (2017)'s approach rest. The coefficients start to become negative after 2001, indicating that the reform did actually have an impact. As expected, Keiser and Shapiro (2017)'s approach slightly underestimates the impact of the Nitrate Directive compared to our approach since it does not take into account the fact that the impact of the Directive slowly accumulates along the river stream. In contrast with our method, Keiser and Shapiro (2017)'s approach does not allow to estimate

0.874 for group 3 and -0.139 $\pm$ 0.845 for group 4. Estimates using a yearly balanced panel instead of a monthly balanced one yield similar results.

dose-response effects because most of the hydrographic zones located at the border of vulnerable zones are covered by the regulation on a small proportion of their area. Finally, Keiser and Shapiro (2017)'s approach is less precise since it focuses on a smaller subset of all the observations. It is nevertheless reassuring that using a different identification strategy yields very similar estimates of the main effect of the Nitrate Directive on nitrate concentrations as our main estimator.

Estimating precision accounting for autocorrelation along river streams

When estimating the precision of the effect of the Nitrate Directive on water quality, we have accounted for the autocorrelation in error terms by clustering standard errors at the hydrographic zone level. In this section, we explore the actual level of autocorrelation using the empirical estimator suggested by Barrios et al. (2012). We test how sensitive our estimates of precision are to the assumption that most autocorrelation takes place within hydrographic zones, using Leung (2020)'s estimator of the covariance matrix on a network.

Figure 19 presents the empirical estimates of spatial and temporal autocorrelation using Barrios et al. (2012)'s estimator detailed in equation (7). The first striking fact that emerges from Figure 19 is how large autocorrelation in the levels of treatment intensity and nitrate concentration is, both over time and over space. Both autocorrelation estimates are of the same order of magnitude as the variance of the variables, and decrease extremely slowly as distance between observations grows over space and time. The second result from Figure 19 is that introducing fixed effects accounts for a large fraction of the autocorrelation between observations, especially over space and especially for nitrate concentrations. Figure 19a shows that spatial autocorrelation in nitrate concentrations decreases as observations are further away from each other along river streams, passing under 0.25 beyond four levels of separation. The difference between levels and residuals of a fixed effect regression is even starker for temporal correlation, as Figure 19b shows. Temporal correlation in the levels of nitrate concentrations is extremely high, close to 1 even with as much as 24 months of separation between observations. Temporal correlation in residuals decreases to a maximum of 0.4 and reaches almost zero at 6 month intervals, which shows that we have been able to capture a large chunk of the covariance between observations with our set of fixed effects. Despite these improvements, autocorrelation in residuals remains large and calls for accounting for it both in the spatial and temporal dimensions when estimating standard errors.

Figure 20 presents the results of estimating the precision of the effect of the Nitrate Directive on nitrate concentration, using traditional Huber-White clustered standard errors estimators along with Leung (2020)'s estimator of the covariance matrix on a network, presented in equation (8), under various assumptions of the structure of autocorrelation. It appears clearly on Figure 20 that ignoring autocorrelation altogether would greatly overestimate precision, by a factor of three approximately. Accounting for spatial correlation along river streams doubles the naive estimate of the standard error. Accounting for temporal correlation between observations from the same station across time increases standard errors by another 50%. Clustering standard errors at the hydrographic zone level yields very similar estimates of precision as the ones obtained using Leung's standard errors accounting for both spatial and temporal correlation. The precision of our main estimates is therefore not affected by accounting for spatial and temporal autocorrelation more finely.

Evidence on diffusion effects, the dose-response relationship and proper specification of the exposure mapping

Until now, we have insisted on the importance of taking into account diffusion effects along river streams when estimating the effect of the Nitrate Directive, without bringing hard evidence that these effects exist. The main piece of evidence that we have is the one presented in Table 13 where we have seen that estimators ignoring diffusion effects either underestimate the effect of the regulation or miss the steepness of the dose-effect relationship. In this section, we present additional evidence in favor of the existence of diffusion effects and of their importance, as well as the existence of a dose-response relationship and of the proper specification of our exposure mapping.

Figure 21 presents the results of randomization-inference tests à la Athey et al. (2018) for the existence of treatment effects, of diffusion effects and of a dose-response relationship. Figure 21a presents the results of the tests of the null hypothesis that there are no direct effects of the Nitrate Directive on the regulated hydrographic zones. The results show strong evidence for rejecting this hypothesis in favor of the existence of treatment effects. Figures 21b and 21c present the results of the tests of the null hypothesis that there are no diffusion effects at distances one and two respectively. Again, both tests provide evidence that these hypotheses can be rejected with a high level of confidence, and thus that the Nitrate Directive has diffusion effects of order one and two. Figure 21d presents the results of the tests of the null hypothesis that there is no dose-response relationship. The alternative is that it is only passing the 25% threshold in treatment intensity that matters for the effects of the Directive to materialize. Here, results are less stark, but the p-value for this hypothesis is 0.1 for both estimators, suggesting that there is some ground in favor of the existence of a dose-response relationship.

Finally, we test the validity of our specification of treatment exposure. Remember that we use the proportion of the watershed upstream of i that is regulated under the Nitrate Directive (or treatment intensity) as our definition of treatment exposure. One implication of that definition of treatment exposure is that the precise location of the regulated areas upstream of i does not matter, as long as the overall treatment intensity is constant. A less restrictive definition of treatment exposure would allow for differential effects of the treatment, depending on the exact distance from i at which the upstream is regulated. One such alternative is to use $\left\{T_i^{u_q}\right\}_{q\in\{0,\dots,Q\}}$, the set of treatment intensities at distances 1 to Q, as defined in equation (2). We thus run the following regression:

$$Y_{sirmt} = \sum_{q=0}^{Q} \psi_q (T_i^{u_q} \times post_t) + \alpha' X_{sirmt} + \delta_s + \gamma_m + \theta_{rt} + \epsilon_{sirmt}. \tag{19}$$

In equation (19), the assumption that our preferred exposure mapping is properly specified can be encoded as the null hypothesis that $\psi_0 = \psi_1 = \cdots = \psi_Q = \psi$. Under this assumption, we can indeed rewrite the first term on the right hand side of equation (19) as $\psi(T_i \times post_t)$, meaning that the effect of the treatment depends only on treatment intensity (the total proportion of the upstream of hydrographic zone i that is regulated under the Nitrate Directive) and not on the precise location where the regulation is implemented. In practice, we estimate equation (19) with $Q = 2$, using all the hydrographic zones that have upstream neighbors at a distance of two upstream zones or more (in order to avoid the confounding influence of the number of neighbors). Note that this approach assumes a linear dose-response relationship, in order to be parsimonious and save on the number of coefficients. Figure 22 presents the estimates of the ψ_q parameters. These coefficients can be interpreted as the effect of moving from zero to 100 percent of the upstream area regulated under the Nitrate Directive. Regulating a hydrographic zone under the Nitrate Directive decreases nitrate concentrations by 2.031±2.744 mg/l in the same zone, by 2.343±2.086 mg/l when the regulated zone is one upstream zone away and by 1.418±0.542 when the regulated zone is two upstream zones away. However imprecise, the size of these coefficients is similar to the impacts we find for moving the totality of the upstream under the Nitrate Directive in our main specifications (see Figure 9 and Table 3). We test the null hypothesis that $\psi_0 = \psi_1 = \psi_2 = \psi$ using a Wald statistic, which, under the null, is distributed as a χ^2_Q. The Wald statistic is equal to 1.898, which, in a χ^2_2 distribution, has p-value 0.387. We thus do not reject the null of a properly specified exposure mapping.

Balanced sample and alternative treatment dates

Our main regressions on water quality are run on an unbalanced sample of monitoring stations with at least one observation before 2000 and at least five measurements per monitoring station. Table 14 and Table 15 present the result of the same specification run on a balanced sample with yearly measurements at the same monitoring stations over the period 1994-2015. Figure 23a presents the sensitivity of the estimates of the impact of the Nitrate Directive on nitrate concentrations to various balanced samples. The number of observations is roughly divided by two after balancing, but the qualitative and quantitative properties of the results remain unchanged.

Our main regressions use 2001 as the official treatment date, and consider all the hydrographic zones classified as vulnerable at any time between 2001 and 2012 as treated. Since there has been some, albeit limited, entry and exit into the list of vulnerable zones, we test the sensitivity of our results to the exact definition of vulnerable zone, always using 2001 as the official treatment date. We also test the sensitivity of our results to a time-varying definition of the treatment group, by including the hydrographic zones in the treated group only in the years in which they are classified as vulnerable. Figure 23b presents the results of these robustness checks. Our results are both qualitatively and quantitatively robust to the exact definition of the treatment group. An interesting pattern seems to emerge: the estimated effects are slightly smaller when using the list of vulnerable zones in 2001 as our treated group and when using a time-varying definition of the treatment group. This result might be explained by the fact that, using only the zones classified as vulnerable in 2001 as treated puts in the control group all the zones that become classified as vulnerable after 2001. Since these latter zones experience an improvement in nitrate concentrations, putting them in the contro group biases downwards the estimate of the impact of the Nitrate Directive on water quality. Using a time-varying definition of the treatment group puts in the control group hydrographic zones that have been excluded from the list of vulnerable zones. Sinxe these latter zones have experienced improvements in water quality, their inclusion in the coontrol group again biases downwards the impact of the Nitrate Directive on water quality.

Land Use Changes

In our main regressions, we have not reported the impact of the Nitrate Directive on land use. It is possible that our results on increasing nitrogen use efficiency, or on increasing water quality, comes from changes in land use. In this section, we estimate the impact of the Nitrate Directive on land use and we look at how the impact of the Nitrate Directive changes when conditioning on land use. We estimate crop areas from the French Agricultural Censuses of 1988, 2000 and 2010. We relate 1988 land use values to the period before the Nitrate Directive and 2000 and 2010 to after the Nitrate Directive.

Figure 24 presents the trends in land use (especially crops) in areas covered and not covered by the Nitrate Directive, while Figure 25 presents the same trends for grassland areas and number of livestock units. The Directive seems to result in an increase in the area in cereals and crops, and a simultaneous decrease in grassland areas and in livestock. The changes seem rather small with respect to the mean values, though. Table 16 confirms this informal analysis. We find that the Nitrate Directive decreased grassland area by 33±8 ha, or 12%, while it increased the area under cereals by 18±1.6 ha. Table 17 and Table 18 report the results of regressions including land use as a control variable. We find that land use changes are unlikely to explain our results: the coefficients of interest remain almost unchanged when controlling for land use.

Wastewater Treatment Plants

At the same time as the Nitrate Directive was implemented, the EU Water Directive required the establishment of wastewater treatment plants along river streams. If the wastewater treatment plants were positioned in a way that is correlated with the zones regulated under the Nitrate Directive, then our results might be biased. We test the importance of wastewater treatment plants as a potential alternative source of improvement of water quality. We use a public database on Urban Wastewater Treatment Plants from the French government website data.gouv.fr providing information on the location of the treatment plants, their opening year and their capacity in terms of population equivalents.

Figure 26 displays the wastewater treatment plants over the period 1994-2015. The total number of treatment plants increases gradually over time, with 4,600 hydrographic zones that did not contain a treatment plant in 1994 to only 2,000 in 2015. We define a treatment variable for sewage water treatment plants: a hydrographic zone belongs to the treated group when a new wastewater treatment plant has opened after 1994, while it belongs to the control group when it has no new plant over the period 1994-2015. We use an event study approach, with hydrographic zones with no treatment station being a reference and each treated zone receiving an indicator depending on the year of treatment, in the interval [-22,22], 0 being the year the wasterwater treatment plant opens.[14] We denote $WastewaterTreatment_{imt}$ the treatment variable for hydrographic zone i in month m and year t.

Figure 27a displays the annual means of nitrate concentrations in watersheds belonging to the wastewater treated group and to the control group. The trends are similar between the two groups until 2000 and then nitrate concentration decreases progressively in the treated group relative to control group. Figure 27b presents the results of an event study regression of the impact of wastewater treatment plants on nitrogen concentrations. We see that the trends in Nitrate concentration remain parallel until the opening of the wastewater treatment plant, and that water quality gradually improves afterwards. Table 19 reports the results of our main regression including the wastewater treatment dummies as control variables. Our results remain unchanged when taking into account this new variable.

6 Discussion

In this section, we put our results into perspective and try to clarify what we learn from them. The first part of this discussion examines the impact of the Nitrate Directive on water quality. The second part considers the impact of the Nitrate Directive on farmers. Finally, the last part looks at the first two parts in relation to each other.

Our results show that the Nitrate Directive has improved water quality and increased biodiversity. First, the Nitrate Directive succeeded in reducing nitrate concentrations in freshwater in France. We estimate that the Nitrate Directive decreased nitrate concentration in water by 1.23±0.27 mg/l, or 8%. There is a clear dose-response relationship with improvements of up to 2.82±0.44 mg/l in hydrographic zones with an upstream watershed regulated at 100% under the Nitrate Directive. We find similar improvements for other indicators of nitrate pollution, such as the concentration of nitrites and ammonium. Second, the Nitrate Directive improved overall water quality beyond the concentration in nitrate and its by-products. We find that the Nitrate Directive decreased the concentration of phosphorus in water, which might be a consequence of the reduction of transfers of organic fertilizers such as manure. As a consequence of the reduction of nitrate and phosphorus concentrations, the Nitrate Directive also reduced eutrophication. We find that the Directive decreased the concentration of Chlorophyll A and chemical oxygen demand and increased dissolved oxygen. Third, we also find improvements in biodiversity, with more fish and more fish species observed, thanks to the Nitrate Directive. Overall, we interpret the improvements

[14] The event study regression is:

$$Nitrate_{simt} = \beta WastewaterTreatment_{imt} + \alpha' X_{simt} + \delta_m^W + \gamma_s^W + \theta_t^W + \epsilon_{simt} \tag{20}$$

where $Nitrate_{simt}$ denotes nitrate concentrations measured by stations s located in hydrographic zone i, in month m and year t. X_{simt} is a matrix of water control variables (quality of measurement, measurement support, portion analyzed, whether the reading is raw or has been controlled, analyzed or validated), δ_m^W denotes month fixed effects, γ_s^W represents monitoring station fixed effects and , θ_t^W are year fixed-effects.

in biodiversity as consequences of the improvements in water quality.

Our results also suggest that the Nitrate Directive has improved the efficiency of farmers' use of nitrogen. First, farmers have planted more nitrogen-fixing crops, in compliance with the Nitrate Directive. This has certainly helped to reduce nitrogen runoff from fields, and contributed to the improvement of water quality. Second, and rather surprisingly, we find no impacts of the Nitrate Directive on the planting of grass-buffer strips, despite being mandated by the Nitrate Directive. This result is probably due to the fact that the planting of grass-buffer strips has been made part of the eco-conditionality of the direct payments that farmers receive under the first pillar of the Common Agricultural Policy in 2001. We see a similar increase in the planting of grass buffer strips in areas not covered by the Nitrate Directive. Third, we find that the Nitrate Directive has increased the proportion of farmers using modern nitrogen management tools, such as the nitrogen balance method that computes the dose of nitrogen to apply as a function of the expected yield and of the amount of nitrogen in the field after winter. We also find that the Nitrate Directive has increased the proportion of farmers analyzing the nitrogen content of their plots after winter, again as required by the Directive. Fourth, we do not find that farmers significantly decreased their nitrogen input as a consequence of the Nitrate Directive. Fifth, we find that total output as measured in nitrogen units has increased, resulting in an increase in nitrogen use efficiency. One possible vehicle for that is the mandatory adoption of soil analysis and of the nitrogen balance method.

Finally, we find evidence that the Nitrate Directive has increased farmers' economic efficiency. We find that the Nitrate Directive increased farmers' total factor productivity, that is, the effectiveness with which farmers convert inputs into outputs. One possible reason for that is the adoption of technical innovations such as soil analysis and the nitrogen balance method that have improved the effectiveness of the use of inputs, especially nitrogen fertilizers. Our finding that the Nitrate Directive has increased farmer's productivity is consistent with the Porter hypothesis that environmental regulation might increase economic efficiency. We can only speculate as to which market or behavioral failures could explain the non-adoption of potentially profitable technologies by farmers. We favor informational biases on the side of farmers as the most liekly explanation. Farmers might underestimate the gains from the adoption of modern nitrogen management technologies. The regulation compels them to adopt an otherwise profitable innovation. Other possible explanations include credit constraints and procrastination due to hyperbolic discounting. It is beyond the scope of this paper to shed light on the precise behavioral mechanisms behind our results. Our results nevertheless suggest that regulations might have unexpected effects not captured under the assumption of perfect markets and perfectly rational and informed agents. In that case, command and control regulations might be more effective than price regulations, as suggested by Allcott (2016).

7 Conclusion

In this paper, we estimate the impact of one of the earliest and most ambitious regulation of nitrogen use in the world, the EU Nitrate Directive. The nitrogen cycle is one of the most disrupted geochemical cycles on earth, mostly as a consequence of farmers' use of synthetic nitrogen fertilizers. The EU Nitrate Directive requires the creation of storage facilities for manure, sets limitations on the amount and timing of nitrogen application, and also mandates the adoption of modern nitrogen management tools in an effort to enhance nitrogen use efficiency. We leverage the geographical and temporal variation in the implementation of the Nitrate Directive to estimate its causal effects on water quality and biodiversity, and on farmers' practices, nitrogen use efficiency, productivity and profits in a Difference In Differences framework. We modify the Difference In Differences estimator to account for the existence of diffusion effects along river streams, and for the non-point-source nature of pollution by nitrates. We gather rich datasets on water quality, the hydrographic network, climate data, farmers' practices and wastewater treatment plants to examine the effects of the Nitrate Directive on an array of outcomes: from water quality with more than 400,000 observations from 2,800 monitoring stations across the country, to farmers' behavior, practices and productivity.

We find that the EU Nitrate Directive reduced the concentration of nitrates in surface water by 1.23 milligrams per liter (mg/l), a decrease of 8%. We find a clear dose-response relationship, with higher impacts where more of the upstream area is covered by the Directive. We find that the Nitrate Directive also improved the physico-chemical state of surface waters, with improvements in terms of nitrites, ammonium, phosphorus, dissolved oxygen and oxygen demand. We find a noticeable improvement in rivers' biological status regarding eutrophication, fish stock and number of fish species. In addition, we show that wastewater treatment plants and land use changes are unlikely to drive our results.

We find that the Nitrate Directive increased the efficiency with which farmers use nitrogen, as well as their overall economic efficiency. We believe that this result stems from the fact that the Nitrate Directive mandated farmers to adopt modern methods of nitrogen management such as nitrogen-fixing crops, soil analysis and the nitrogen balance method, that might have improved the effectiveness of the use of inputs, especially nitrogen fertilizers.

Our result that the Nitrate Directive might have increased farmers' productivity is compatible with the Porter hypothesis that suggests that environmental regulation might increase economic efficiency. We can only speculate as to which market or behavioral failures could explain farmers' non-adoption of potentially profitable technologies. We see farmers' informational biases as the most liekly explanation. Farmers might underestimate the gains from the adoption of modern nitrogen management technologies. If farmers do indeed have biased views about new technologies, then command and control regulations such as the Nitrate Directive might be more effective than price regulations.

On the methodological front, we provide tools for defining, identifying and estimating treatment effects with diffusion effects in a Difference-In-Differences framework. These tools serve to measure the extent of auto-correlation in the data, fine-tune the estimation of precision using the map of the hydrographic network, and implement randomization tests for the existence of diffusion effects and for their shape. These tools could be of interest for similar applications of the Difference-In-Differences method where diffusion effects are likely, such as air pollution, contagious diseases, migration, traffic, etc. We find that ignoring the diffusion effects of the policy would bias downwards the classical DID estimator and the more recent geographical discontinuity estimator of Keiser and Shapiro (2017). These estimators would also miss the steepness of the dose-effect relationship and thus would underestimate the importance of cumulating the regulation over the entire upstream watershed to maximize its effects.

References

Abadie, A. (2005). Semiparametric Difference-in-Differences Estimators. *The Review of Economic Studies 72*(1), 1–19.

Allcott, H. (2016). Paternalism and energy efficiency: An overview. *Annual Review of Economics 8*(1), 145–176.

Ambec, S., M. A. Cohen, S. Elgie, and P. Lanoie (2013). The porter hypothesis at 20: can environmental regulation enhance innovation and competitiveness? *Review of Environmental Economics and Policy 7*(1), 2–22.

Aronow, P. M. and C. Samii (2017). Estimating average causal effects under general interference, with application to a social network experiment. *Annals of Applied Statistics 11*(4), 1912–1947. Publisher: Institute of Mathematical Statistics.

Athey, S., D. Eckles, and G. W. Imbens (2018). Exact p-Values for Network Interference. *Journal of the American Statistical Association 113*(521), 230–240.

Athey, S. and G. W. Imbens (2021). Design-based analysis in Difference-In-Differences settings with staggered adoption. *Journal of Econometrics*.

Banerjee, A., A. G. Chandrasekhar, E. Duflo, and M. O. Jackson (2013). The Diffusion of Microfinance. *Science 341*(6144), 1236498–1236498.

Barigozzi, M. and C. Brownlees (2019). NETS: Network estimation for time series. *Journal of Applied Econometrics 34*(3), 347–364.

Barrios, T., R. Diamond, G. W. Imbens, and M. Kolesár (2012). Clustering, Spatial Correlations, and Randomization Inference. *Journal of the American Statistical Association 107*(498), 578–591.

Barrows, G., H. Ollivier, M. Jegard, and R. Calel (2021). Market Power & Incomplete Regulation: An Application to the EU ETS. Technical report.

Bayramoglu, B., R. Chakir, and A. Lungarska (2019). Impacts of Land Use and Climate Change on Freshwater Ecosystems in France. *Environmental Modeling & Assessment*.

Borusyak, K. and P. Hull (2021). Non-Random Exposure to Exogenous Shocks: Theory and Applications. Technical report.

Borusyak, K. and X. Jaravel (2017). Revisiting Event Study Designs. SSRN Scholarly Paper ID 2826228, Social Science Research Network, Rochester, NY.

Brainerd, E. and N. Menon (2014). Seasonal effects of water quality: The hidden costs of the green revolution to infant and child health in india. *Journal of Development Economics 107*, 49–64.

Brentrup, F. and J. Lammel (2016). Nitrogen use efficiency, nitrogen balance, and nitrogen productivity - a combined indicator system to evaluate nitrogen use in crop production systems. In *International Nitrogen Initiative Conference: Solutions to Improve Nitrogen Use Efficiency for the World*, pp. 4–8.

Cai, J., A. De Janvry, and E. Sadoulet (2015). Social Networks and the Decision to Insure. *American Economic Journal: Applied Economics 7*(2), 81–108.

Callaway, B. and P. H. C. Sant'Anna (2020). Difference-in-Differences with multiple time periods. *Journal of Econometrics*.

Canfield, D. E., A. N. Glazer, and P. G. Falkowski (2010). The evolution and future of earth's nitrogen cycle. *Science 330*(6001), 192–196.

Chabé-Ferret, S. (2015). Analysis of the bias of Matching and Difference-in-Difference under alternative earnings and selection processes. *Journal of Econometrics 185*(1), 110–123.

Chabé-Ferret, S. (2017). Should We Combine Difference In Differences with Conditioning on Pre-Treatment Outcomes?

de Chaisemartin, C. and X. D'Haultfœuille (2020). Two-Way Fixed Effects Estimators with Heterogeneous Treatment Effects. *American Economic Review 110*(9), 2964–2996.

Delgado, M. S. and R. J. G. M. Florax (2015). Difference-in-differences techniques for spatial data: Local autocorrelation and spatial interaction. *Economics Letters 137*, 123–126.

Deryugina, T., G. Heutel, N. H. Miller, D. Molitor, and J. Reif (2019). The Mortality and Medical Costs of Air Pollution: Evidence from Changes in Wind Direction. *American Economic Review 109*(12), 4178–4219.

Diaz, R. J. and R. Rosenberg (2008). Spreading dead zones and consequences for marine ecosystems. *Science 321*(5891), 926–929.

Ebenstein, A. (2012). The consequences of industrialization: evidence from water pollution and digestive cancers in china. *Review of Economics and Statistics 94*(1), 186–201.

Erisman, J. W., M. A. Sutton, J. Galloway, Z. Klimont, and W. Winiwarter (2008). How a century of ammonia synthesis changed the world. *Nature Geoscience 1*(10), 636–639.

EU Nitrogen Expert Panel (2015). Nitrogen Use Efficiency (NUE) - an indicator for the utilization of nitrogen in agriculture and food systems. Technical report, Wageningen University, Wageningen, Netherlands.

Galloway, J. N., J. D. Aber, J. W. Erisman, S. P. Seitzinger, R. W. Howarth, E. B. Cowling, and B. J. Cosby (2003, April). The Nitrogen Cascade. *BioScience 53*(4), 341–356.

Goodman-Bacon, A. (2021). Difference-in-Differences with Variation in Treatment Timing. *Journal of Econometrics*.

Greenstone, M. and R. Hanna (2014). Environmental regulations, air and water pollution, and infant mortality in india. *American Economic Review 104*(10), 3038–72.

Greenstone, M., J. A. List, and C. Syverson (2012). The Effects of Environmental Regulation on the Competitiveness of U.S. Manufacturing. Working Paper 18392, National Bureau of Economic Research.

He, G., S. Wang, and B. Zhang (2020). Watering Down Environmental Regulation in China. *The Quarterly Journal of Economics 135*(4), 2135–2185.

Heckman, J. J., H. Ichimura, and P. E. Todd (1997). Matching as an Econometric Evaluation Estimator: Evidence from Evaluating a Job Training Programme. *The Review of Economic Studies 64*(4), 605–654.

Imbens, G. W. and D. B. Rubin (2015). *Causal Inference for Statistics, Social, and Biomedical Sciences: An Introduction.* Cambridge: Cambridge University Press.

Imbert, C. and J. Papp (2020). Short-term Migration, Rural Public Works, and Urban Labor Markets: Evidence from India. *Journal of the European Economic Association 18*(2), 927–963.

Keiser, D. A. and J. S. Shapiro (2017). Consequences of the clean water act and the demand for water quality. *The Quarterly Journal of Economics*.

Lassaletta, L., G. Billen, B. Grizzetti, J. Anglade, and J. Garnier (2014). 50 year trends in nitrogen use efficiency of world cropping systems: the relationship between yield and nitrogen input to cropland. *Environmental Research Letters 9*(10), 105011.

Leach, A. M., J. N. Galloway, A. Bleeker, J. W. Erisman, R. Kohn, and J. Kitzes (2012). A nitrogen footprint model to help consumers understand their role in nitrogen losses to the environment. *Environmental Development 1*(1), 40–66.

Leung, M. P. (2020). Treatment and Spillover Effects Under Network Interference. *Review of Economics and Statistics*.

Lundberg, J. O., E. Weitzberg, J. A. Cole, and N. Benjamin (2004). Nitrate, bacteria and human health. *Nature Reviews Microbiology 2*(7), 593.

Lungarska, A. and P. Jayet (2014). Nitrate pollution and differentiation of input-based tax applied to france. *Environmental and Resource Economics 69*(1), 1–21.

Manresa, E. (2016). Estimating the structure of social interactions using panel data. Technical report, MIT Sloan.

Manski, C. F. (2013). Identification of treatment response with social interactions. *The Econometrics Journal 16*(1), S1–S23.

Mateo-Sagasta, J., S. M. Zadeh, H. Turral, and J. Burke (2017). Water pollution from agriculture: a global review. executive summary.

Miguel, E. and M. Kremer (2004). Worms: Identifying Impacts on Education and Health in the Presence of Treatment Externalities. *Econometrica 72*(1), 159–217.

Missirian, A. (2019). Yes, in Your Backyard: Forced Technological Adoption and Spatial Externalities.

OECD (2012). *Water quality and agriculture: meeting the policy challenge. OECD Studies on Water.* Organisation for Economic Co-operation and Development (OECD).

Pavan, G., S. Calligaris, and F. M. D'Arcangelo (2019). The Impact of the European Carbon Market on Firm Productivity: Evidence from Italian Manufacturing Firms. Technical report.

Porter, M. E. and C. Van der Linde (1995). Toward a new conception of the environment-competitiveness relationship. *Journal of Economic Perspectives 9*(4), 97–118.

Rockstrom, J., W. Steffen, K. Noone, A. Persson, F. S. Chapin, E. F. Lambin, T. M. Lenton, M. Scheffer, C. Folke, H. J. Schellnhuber, B. Nykvist, C. A. de Wit, T. Hughes, S. van der Leeuw, H. Rodhe, S. Sorlin, P. K. Snyder, R. Costanza, U. Svedin, M. Falkenmark, L. Karlberg, R. W. Corell, V. J. Fabry, J. Hansen, B. Walker, D. Liverman, K. Richardson, P. Crutzen, and J. A. Foley (2009, September). A safe operating space for humanity. *Nature 461*(7263), 472–475.

Smil, V. (2000). *Enriching the Earth.* MIT Press.

Sun, L. and S. Abraham (2020). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics*.

Syverson, C. (2011). What Determines Productivity? *Journal of Economic Literature 49*(2), 326–365.

UNEP (2019, April). Frontiers 2018/19: Emerging Issues of Environmental Concern. Section: publications.

Wu, J., R. M. Adams, C. L. Kling, and K. Tanaka (2004). From Microlevel Decisions to Landscape Changes: An Assessment of Agricultural Conservation Policies. *American Journal of Agricultural Economics 86*(1), 26–41.

WWAP (2013). *The United Nations World Water Development Report 2013. United Nations World Water Assessment Programme (WWAP).* Paris, United Nations Educational, Scientific and Cultural Organization.

A Proofs

A.1 Structural model of water quality along a river stream

In this section, we introduce a simple structural model of water quality along a river stream that is compatible with Assumption 2 and with equation (4). We model water quality in an hydrographic zone i at date t $Y_{i,t}$ as a weighted average between the quality of water that has ran off from the fields and lands located within this hydrographic zone $Y^*_{i,t}$ and the average quality that stems from the nearest upstream hydrographic zones $\sum_{j:d(i,j)=1} \tilde{w}^i_j Y_{j,t}$. The various components of the model are defined as follows:

$$Y_{i,t} = w_i Y^*_{i,t} + \sum_{j:d(i,j)=1} \tilde{w}^i_j Y_{j,t} \tag{21}$$

$$w_i = \frac{a_{i,i}}{\sum_{l=1}^N a_{l,i}} \tag{22}$$

$$\tilde{w}^i_j = \frac{\sum_{l=1}^N a_{l,j}}{\sum_{l=1}^N a_{l,i}} \tag{23}$$

$$Y^*_{i,t} = \mu_i + \delta_t + \alpha D_{i,t} + \epsilon_{i,t}. \tag{24}$$

The weights we choose are proportional to the area of each zone in the upstream watershed of zone i, which is a way to approximate the quantity of water that comes from each zone and flows to i. The quality of the water running off from fields and lands located in zone i depends on a zone fixed effect μ_i that captures permanent (at least over the duration of our sample) determinants of water quality in this zone, such as land quality, but also the average types of crops, fertilizers and number of animals that are generally found in the fields located in the zone. The time fixed effect δ_t captures the changes in water quality that are specific to each year but similar across all zones (or all zones in a region when this effect is region specific). They capture changes in precipitation, but also in prices of inputs and outputs that might change how much nitrogen is sprayed on fields. $\alpha D_{i,t}$ captures the effect of the regulation by the Nitrate Directive on the water that runs off fields regulated under the Directive. $\epsilon_{i,t}$ captures other idiosyncratic shocks to water quality specific to zone i at date t.

We can now show that this model can be written as an additive separable model where treatment exposure is summarized by a treatment intensity index as the one we define in equation (1). By iterative substitution, we indeed have:

$$Y_{i,t} = \underbrace{w_i\mu_i + \sum_{j:d(i,j)=1} \tilde{w}_j^i \tilde{\mu}_j}_{\tilde{\mu}_i} + \delta_t \underbrace{\left(w_i + \sum_{j:d(i,j)=1} \tilde{w}_j^i \right)}_{1}$$

$$+ \alpha \underbrace{\left(w_i D_{i,t} + \sum_{j:d(i,j)=1} \tilde{w}_j^i T_{j,t} \right)}_{T_{i,t}} + \underbrace{w_i \epsilon_{i,t} + \sum_{j:d(i,j)=1} \tilde{w}_j^i \tilde{\epsilon}_{j,t}}_{\tilde{\epsilon}_{i,t}}, \tag{25}$$

an equation similar to our equation (4) and compatible with Assumption 2.

A.2 Proof of Theorem 1

For simplicity, we keep the conditioning on $X_{i,t}$ implicit all along. The proof can be separated into two steps. In the first step, we show that the assumptions that we have made imply a version of the parallel trend assumptions. In a second step we show that, under this condition, our DID estimator identifies the average effect of treatment exposure on the treated. Let us first state the lemma:

Lemma 1 (Parallel trends) *Under Assumptions 1, 2, 3, 4 and 5, the Parallel Trends Assumption holds:*

$$\mathbb{E}[Y_{i,k+\tau}(0) - Y_{i,k-\tau'}(0)|\Delta_i = d] = \mathbb{E}[Y_{i,k+\tau}(0) - Y_{i,k-\tau'}(0)|\Delta_i = 0].$$

Proof. Under Assumption 1, we can write potential outcomes as a function of $\tilde{\Delta}_{i,t}$. Under Assumptions 2, 3, 4 and 5, we have:

$$\begin{aligned}
\mathbb{E}[Y_{i,k+\tau}(0) - Y_{i,k-\tau'}(0)|\Delta_i] &= \mathbb{E}[g(\mu_i) + h(\delta_{k+\tau}) + m(0, \mu_i, \delta_{k+\tau}) + \epsilon_{i,k+\tau}|\Delta_i] \\
&\quad - \mathbb{E}[g(\mu_i) + h(\delta_{k-\tau'}) + m(0, \mu_i, \delta_{k-\tau'}) + \epsilon_{i,k-\tau'}|\Delta_i] \\
&= h(\delta_{k+\tau}) - h(\delta_{k-\tau'}) + \mathbb{E}[\epsilon_{i,k+\tau} - \epsilon_{i,k-\tau'}|\Delta_i] \\
&= h(\delta_{k+\tau}) - h(\delta_{k-\tau'}),
\end{aligned}$$

where the first equality stems from Assumptions 2 and 5, the second equality stems from Assumption 4 and the last equality stems from the Law of Iterated Expectations and Assumption 3: $\mathbb{E}[\epsilon_{i,t}|\Delta_i] = \mathbb{E}[\mathbb{E}[\epsilon_{i,t}|\Delta_i, \mu_i, \delta_t]|\Delta_i] = 0$, $\forall t$. As a consequence, $\mathbb{E}[Y_{i,k+\tau}(0) - Y_{i,k-\tau'}(0)|\Delta_i]$ does not depend on Δ_i under Assumptions 1, 2, 3, 4 and 5, which proves the result. ■

The proof of the theorem follows from Lemma 1 since our DID estimator can be written as follows:

$$
\begin{aligned}
DID^Y_{k+\tau,k-\tau'}(d) &= \mathbb{E}[Y_{i,k+\tau} - Y_{i,k-\tau'}|\Delta_i = d] - \mathbb{E}[Y_{i,k+\tau} - Y_{i,k-\tau'}|\Delta_i = 0] \\
&= \mathbb{E}[Y_{i,k+\tau}(\Delta_i) - Y_{i,k+\tau}(0)|\Delta_i = d] \\
&\quad + \mathbb{E}[Y_{i,k+\tau}(0) - Y_{i,k-\tau'}(0)|\Delta_i = d] - \mathbb{E}[Y_{i,k+\tau}(0) - Y_{i,k-\tau'}(0)|\Delta_i = 0],
\end{aligned}
$$

which is equal to $TT^Y_{k+\tau}(d)$ when the Parallel Trends Assumption holds.

B Figures

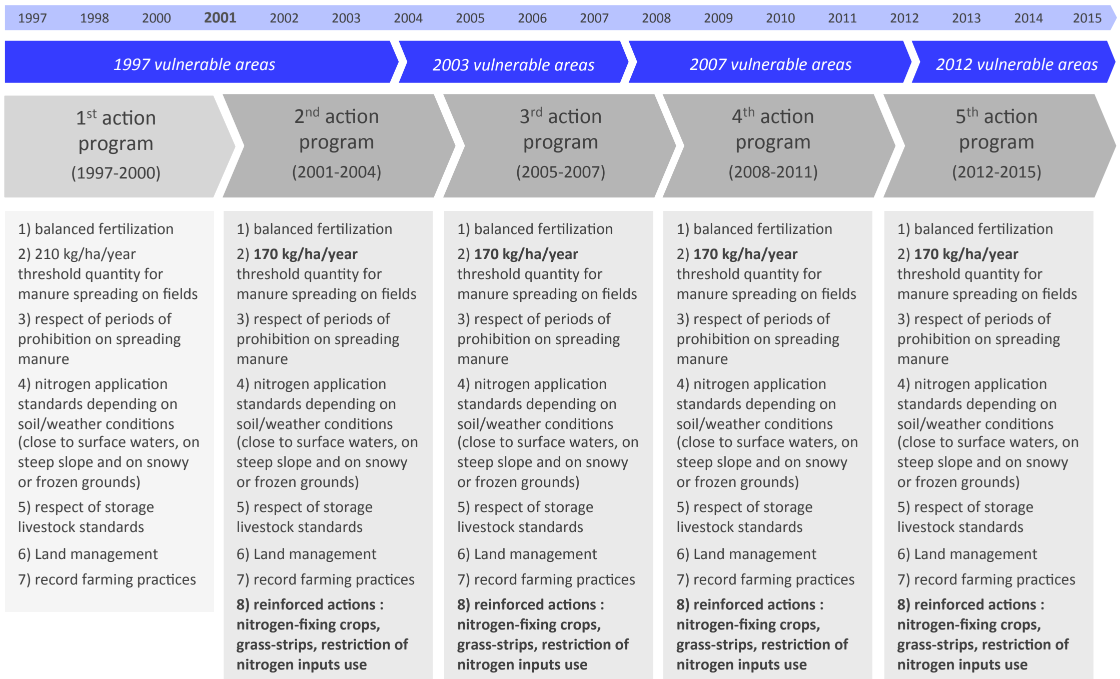


Figure 1: Historical timeline of the action programs of the EU Nitrate Directive

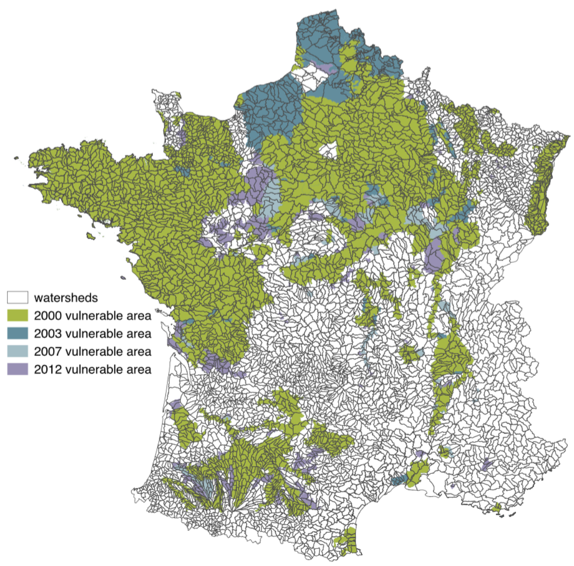
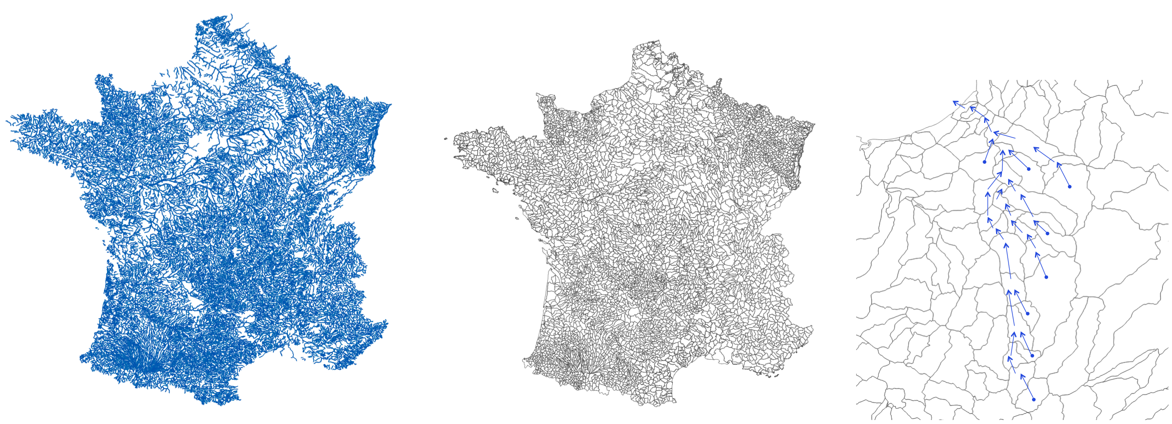


Figure 2: Map of the vulnerable zones from 2000 to 2012



(a) Rivers (b) Hydrographic zones (c) Example of network

Figure 3: French hydrographic network

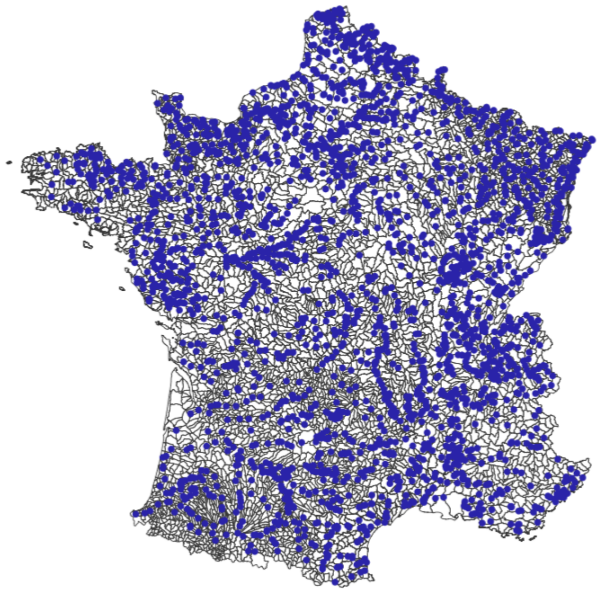
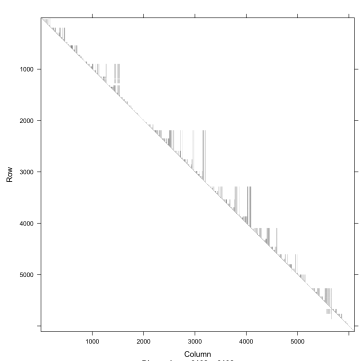
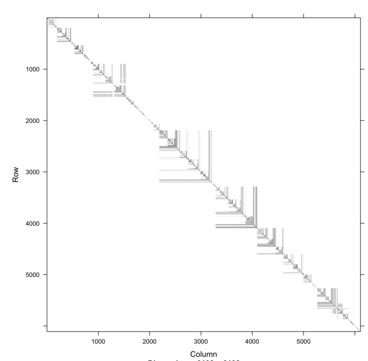


Figure 4: Water quality monitoring stations included in the dataset



(a) A



(b) G

Figure 5: A and G matrices for the French hydrographic network

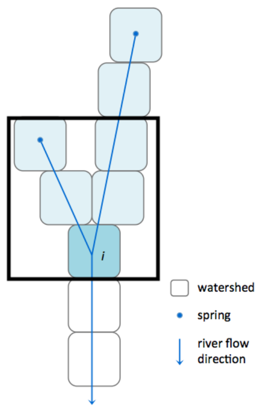
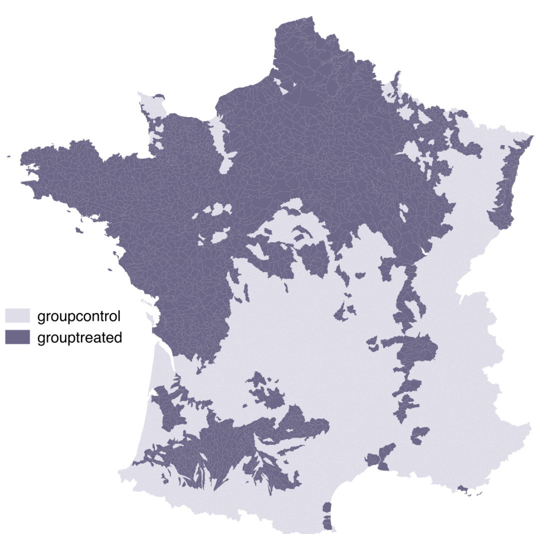
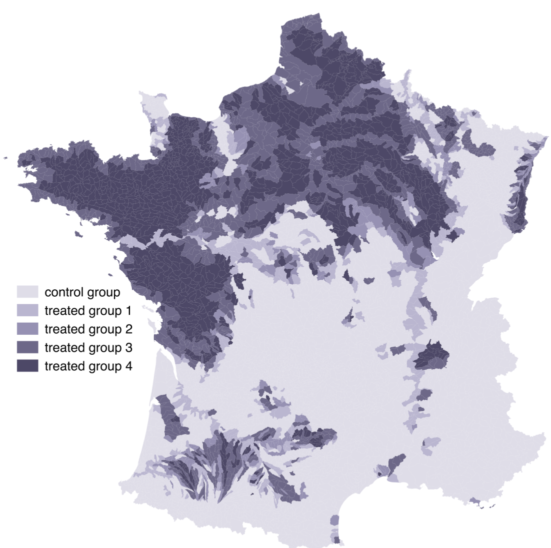


Figure 6: Example of arborescence

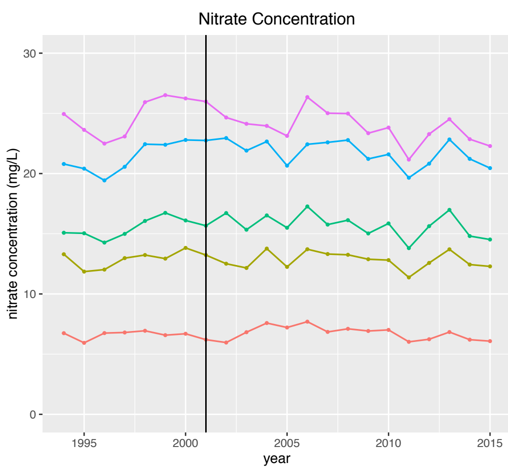


(a) 25% Threshold Treatment Group

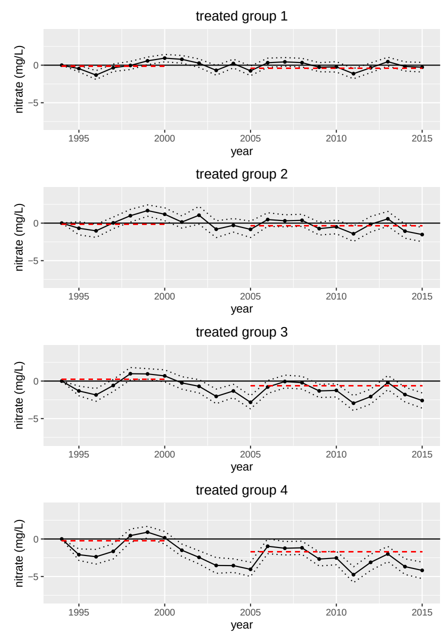


(b) 5 Intensity Treatment Groups

Figure 7: Map of treatment intensity at the watershed level



(a) Levels of nitrate concentration



(b) Trends in nitrate concentration

Figure 8: Nitrate concentrations in surface water in control and treated watersheds

Note: Annual nitrate concentration in (a) and (b) in mg/L. Figure (a) represents average annual nitrate concentration by level of treatment intensity ([0%,25%] for the control group and]25%,50%],]50%,75%],]75%,100%[and 100% for the treated groups 1, 2, 3 and 4 respectively). Figure (b) depicts regression coefficients with year × hydrographic region, month and station fixed effects for each treated group with respect to the control group along with 95% confidence intervals clustered at the hydrographic zone level. The horizontal red dashed line represents pre and post treatment coefficient means.

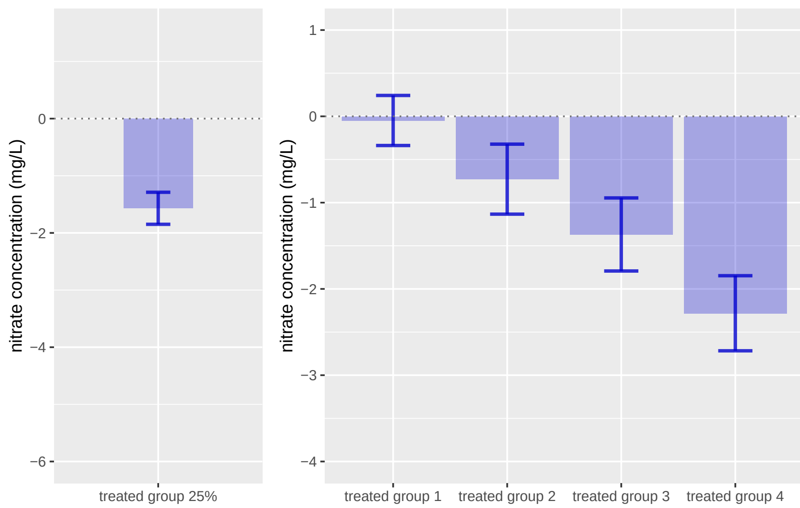
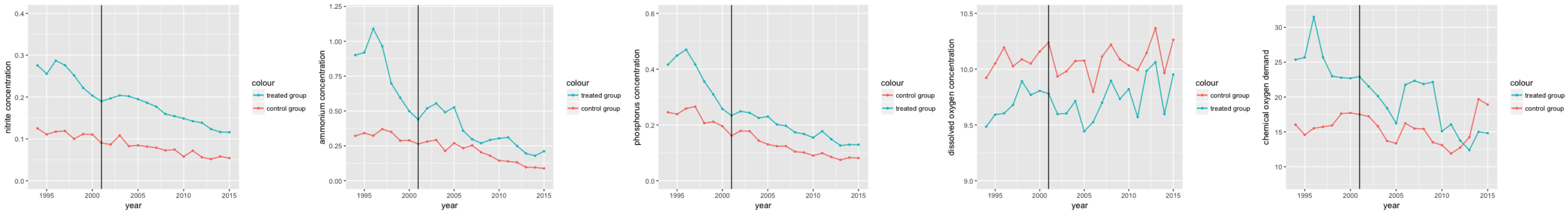
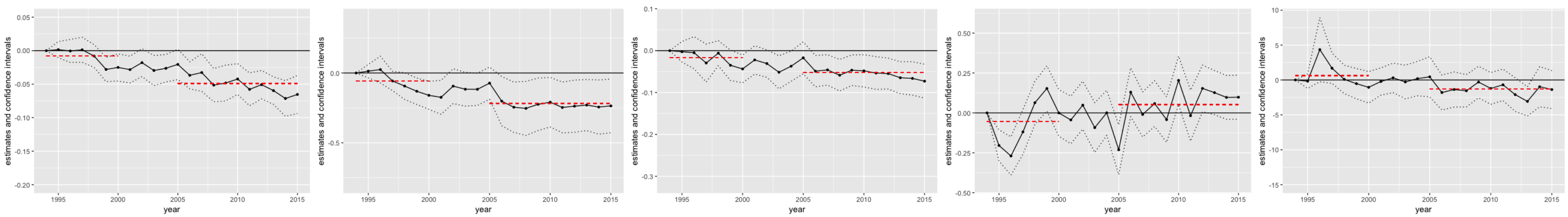


Figure 9: Impact of the Nitrate Directive on nitrate concentration in surface water (mg/l)

Note: Coefficients with 95% confidence intervals using standard errors clustered at the hydrographic zone level. Estimated treatment impacts on nitrate concentration (mg/L) from equation (4) with *25%-threshold treatment* definition (left) and *5-intensity treatment* definition (right).



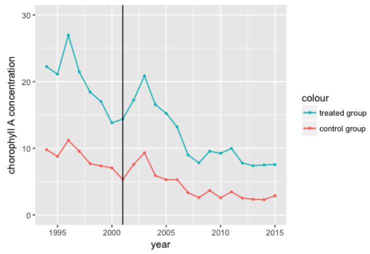
(a) Nitrites (means) (b) Ammonium (means) (c) Phosphorus (means) (d) Dissolved Oxygen (means) (e) Chemical Oxygen Demand (means)



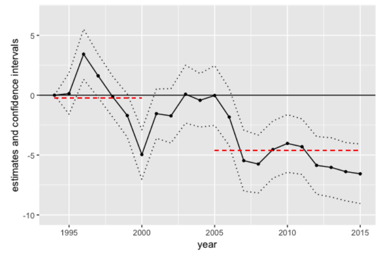
(f) Nitrites (trends) (g) Ammonium (trends) (h) Phosphorus (trends) (i) Dissolved Oxygen (trends) (j) Chemical Oxygen Demand (trends)

Figure 10: Annual means by treatment group (top graphs) and trends relative to the control group (bottom graphs) for physico-chemical outcomes

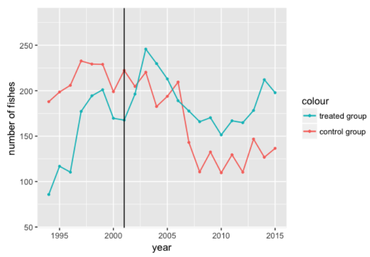
Note: On the top, annual concentrations in mg/L (except Phosphorus in μg/l) for the treated and control groups defined by the *25%-threshold treatment* definition ([0%,25%] for the control group and]25%,100%] for the treated group). On the bottom, regression coefficients with year $\times$ hydrographic region, month and station fixed effects for the treated group with respect to the control group with 95% confidence intervals clustered at the hydrographic zone level. The horizontal red dashed lines represents pre and post treatment coefficient means.



(a) Chlorophyll A (means)

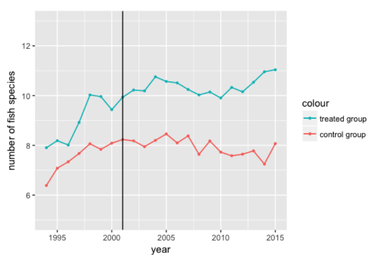


(b) Chlorophyll A (trends)

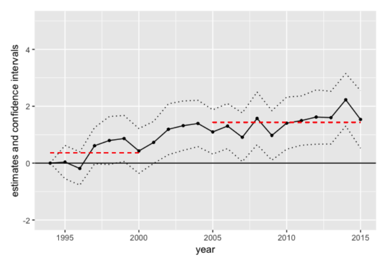


(c) Number of fish (means)

(d) Number of fish (trend)



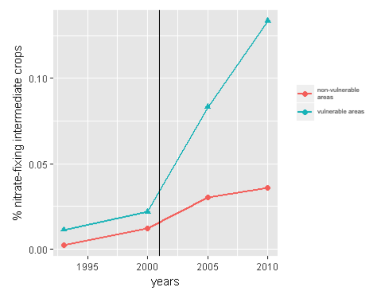
(e) Number of fish species (means)



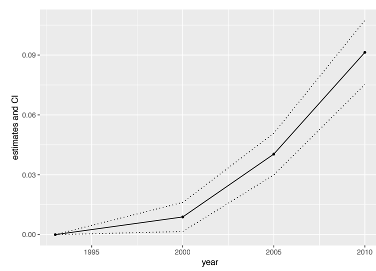
(f) Number of fish species (trends)

Figure 11: Annual means by treatment group (left graphs) and trends relative to the control group (right graphs) for biological outcomes

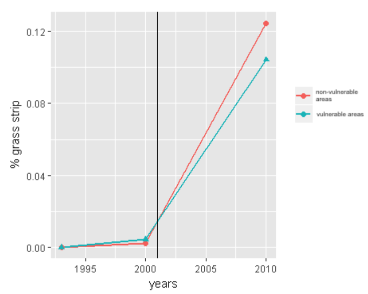
Note: On the left, annual concentrations in Chlorophyll A in μg/l and number of fish and number of fish species for the treated and control groups defined by the *25%-threshold treatment* definition ([0%,25%] for the control group and]25%,100%] for the treated group). On the right, regression coefficients with year $\times$ hydrographic region, month and station fixed effects for the treated group with respect to the control group with 95% confidence intervals clustered at the hydrographic zone level. The horizontal red dashed lines represents pre and post treatment coefficient means.



(a) Nitrate fixing crops (means)



(b) Nitrate fixing crops (trends)

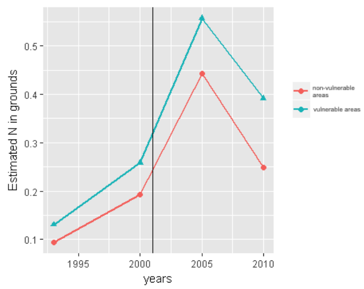


(c) Grass buffer strips (means)

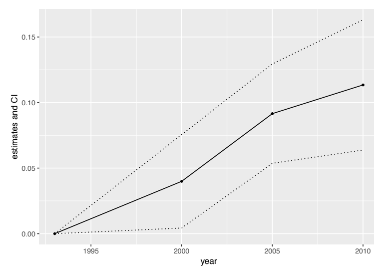
(d) Grass buffer strips (trends)

Figure 12: Annual means by treatment group (left graphs) and trends relative to the control group (right graphs) for nitrate fixing crops and grass buffer strips

Note: On the left, percentage of plots under nitrate-fixing crops and surrounded by grass buffer strips, depending on whether they are located in a vulnerable zone or not. On the right, regression coefficients with year and treatment group fixed effects for the treated group with respect to the control group with 95% confidence intervals clustered at the commune level.

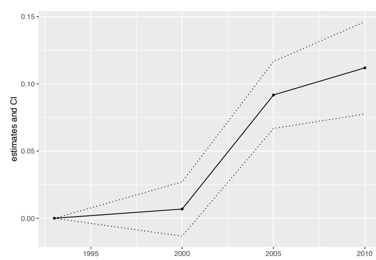


(a) N estimated (means)



(b) N estimated (means)

(c) N adjusted after winter (means)

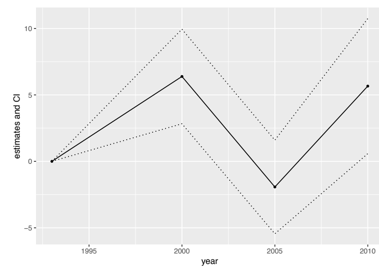


(d) N adjusted after winter (trends)

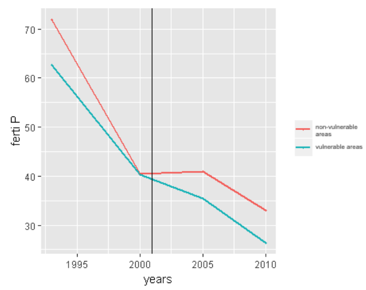
Figure 13: Annual means by treatment group (left graphs) and trends relative to the control group (right graphs) of the proportions of farmers estimating nitrogen content in the soil and of farmers adjusting their level of nitrogen after the end of winter using the nitrogen balance method.

Note: On the left, percentage of plots where farmers estimate the nitrogen content after the end of winter and use this estimate to adjust their choice of fertilizer with the nitrogen balance method, depending on whether they are located in a vulnerable zone or not. On the right, regression coefficients with year and treatment group fixed effects for the treated group relative to the control group, with 95% confidence intervals clustered at the commune level.

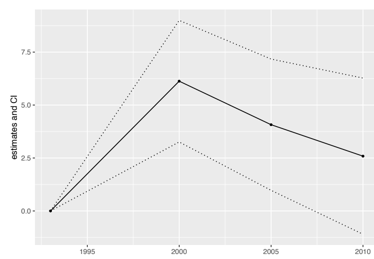
(a) N mineral fertilizer (means)



(b) N mineral fertilizer (trends)

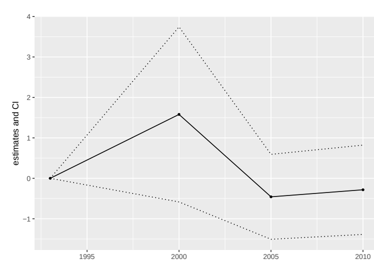


(c) P mineral fertilizer (means)



(d) P mineral fertilizer (trends)

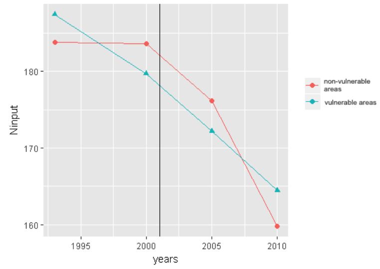
(e) Manure (means)



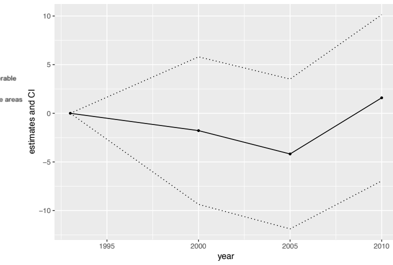
(f) Manure (trends)

Figure 14: Annual means by treatment group (left graphs) and trends relative to the control group (right graphs) of fertilizer use

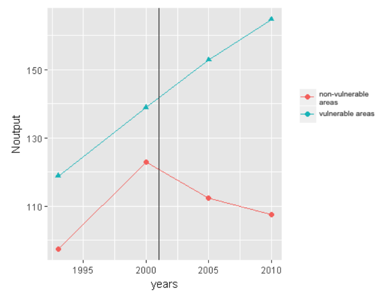
Note: On the left, level of fertilizers (in kgN/ha and kgP/ha) applied on plots depending on whether they are located in a vulnerable zone or not. On the right, regression coefficients with year and treatment group fixed effects for the treated group with respect to the control group with 95% confidence intervals clustered at the commune level.



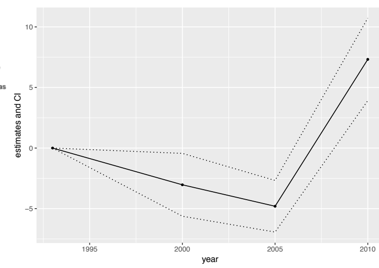
(a) N input (means)



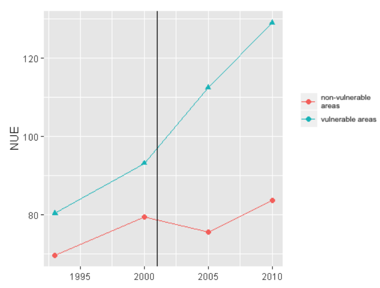
(b) N input (trends)



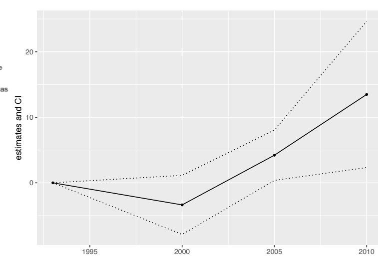
(c) N output (means)



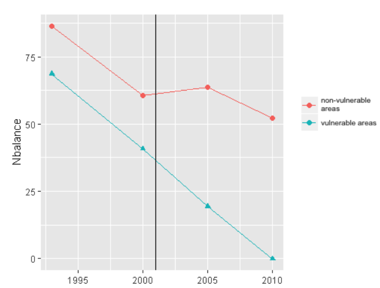
(d) N output (trends)



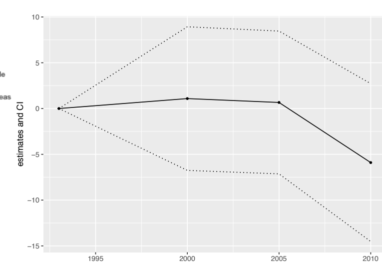
(e) NUE (means)



(f) NUE (trends)



(g) N balance (means)



(h) N balance (trends)

Figure 15: Annual means by treatment group (left graphs) and trends relative to the control group (right graphs) of nitrogen input, output, balance and nitrogen use efficiency

Note: On the left, level of N input, output and balance (in kgN/ha) and NUE on plots depending on whether they are located in a vulnerable zone or not. On the right, regression coefficients with year and treatment group fixed effects for the treated group with respect to the control group, with 95% confidence intervals clustered at the commune level.

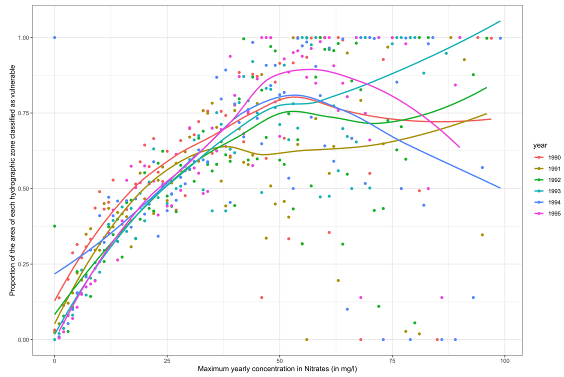
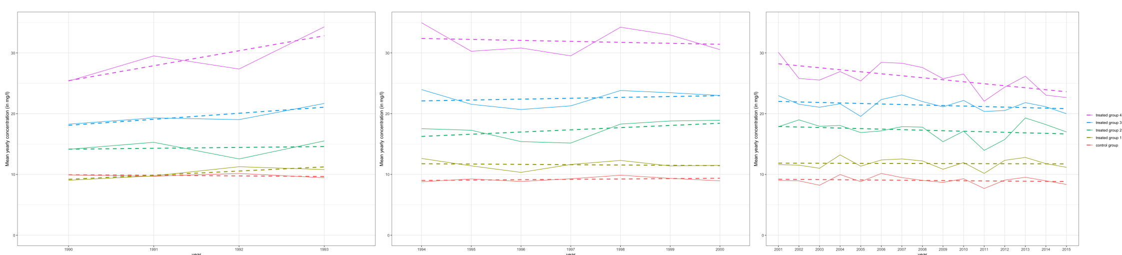


Figure 16: Proportion of area in a vulnerable zone and maximum yearly concentration in nitrates

Note: For each year, we compute the maximum concentration registered in each hydrographic zone and relate it to the proportion of its area that is covered by a vulnerable zone. The fitted curves are obtained by local linear regression.



(a) Before 1993 (b) Between 1994 and 2000 (c) After 2001

Figure 17: Trends in nitrate concentration over time

Note: Estimates of trends in nitrate concentration over time in each of the $5 - intensity$ treatment groups. Yearly means are estimated using a balanced panel at the monthly level. Dashed lines are the best linear fit through each set of data points.

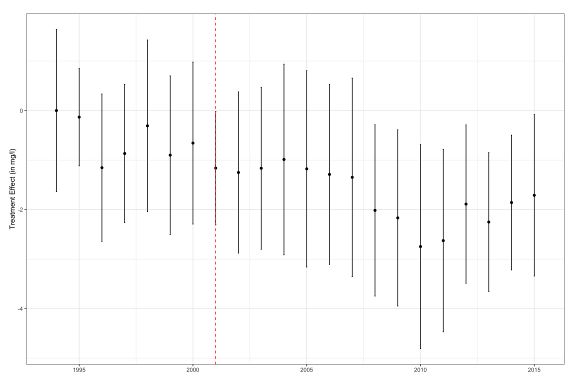
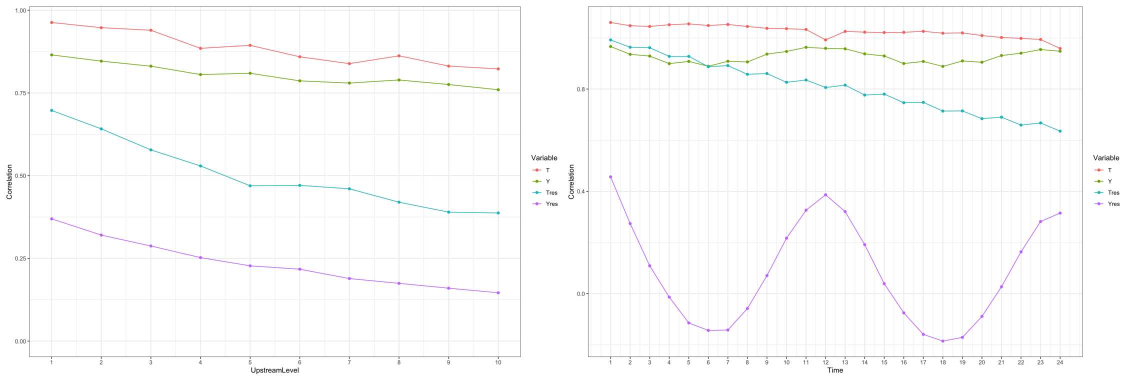


Figure 18: Trends in Nitrate concentration in vulnerable zones relative to neighboring non-vulnerable zones using Keiser and Shapiro (2017)'s approach

Note: Trends in Nitrate concentration in vulnerable zones relative to neighboring non-vulnerable zones using Keiser and Shapiro (2017)'s approach. We provide estimates obtained using equation (6), replacing the $post_t$ dummy by a set of annual dummies. The red dotted line indicates the treatment date. Standard errors are clustered at the hydrographic zone level. Precision is shown as 95% confidence intervals.



(a) Spatial autcorrelation

(b) Temporal autcorrelation

Figure 19: Empirical autocorrelation in nitrate concentrations

Note: Estimates of the empirical autocorrelation in nitrate concentrations obtained using the formula delineated in equation (7). T stands for treatment intensity in levels, while T_{res} stands for the residual of treatment intensity from a regression of treatment intensity on month, station, and year×region fixed effects. Y stands for nitrate concentrations in levels and Y_{res} stands for the residual from a regression of nitrate concentrations on month, station, and year×region fixed effects. Each covariance is scaled by the variance of the variable of interest. "UpstreamLevel" refers to the distance between observations on the hydrographic network. "Time" is measured in months separating observations.

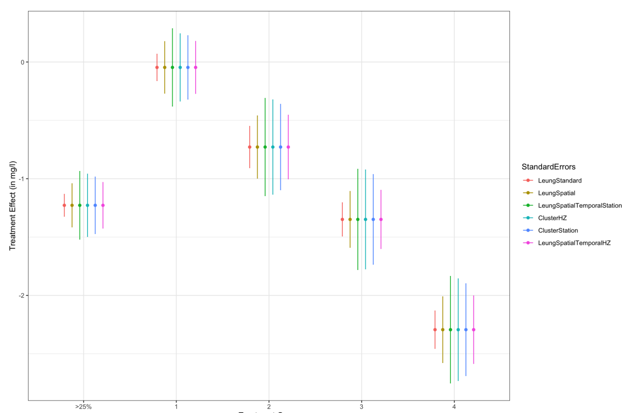
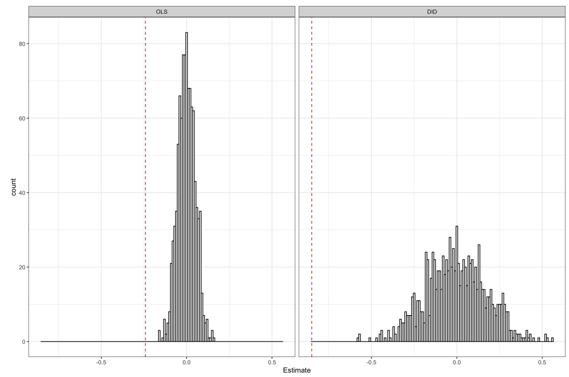
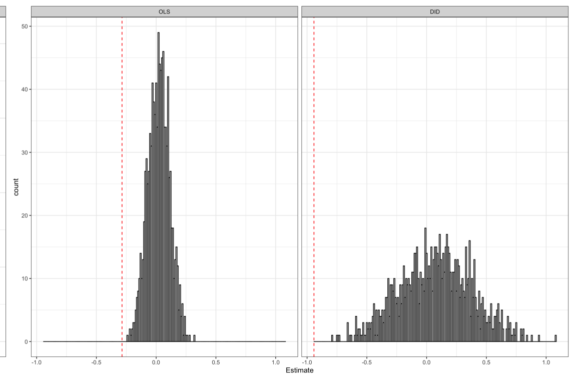


Figure 20: Sensitivity of the precision of the effect of the Nitrate Directive on nitrate concentration as a function of the assumed structure of autocorrelation

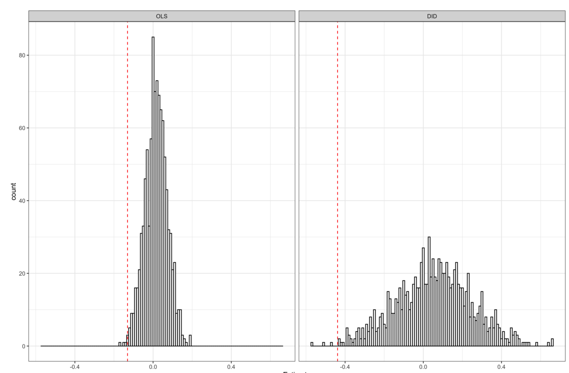
Note: Estimates of the precision of the effect of the Nitrate Directive on nitrate concentration as a function of the assumed structure of autocorrelation using the Leung estimator presented in equation (8). ">25%" refers to the effect of the treatment defined by the *25%-threshold treatment* definition ([0%,25%] for the control group and]25%,100%] for the treated group) while "1", "2", "3" , "4" refer to the *5-intensity treatment* ([0%,25%] for the control group and]25%,50%],]50%,75%],]75%,100%[and 100% for the treated groups). "LeungStandard" refers to the Leung estimates assuming a total absence of autocorrelation between observations, "LeungSpatial" refers to the Leung estimates accounting for autocorrelation along river streams, "LeungSpatialTemporalStation" refers to the Leung estimates accounting for spatial correlation along river streams and for temporal correlation between stations across time, and "LeungSpatialTemporalHZ" refers to the Leung estimates accounting for spatial correlation along river streams and for temporal correlation between hydrographic zones across time. "ClusterHZ" refers to classical Huber-White standard errors clustered at the hydrographic zone level, while "ClusterStation" refers to standars errors clustered at the station level. Precision is presented as 95% confidence intervals.



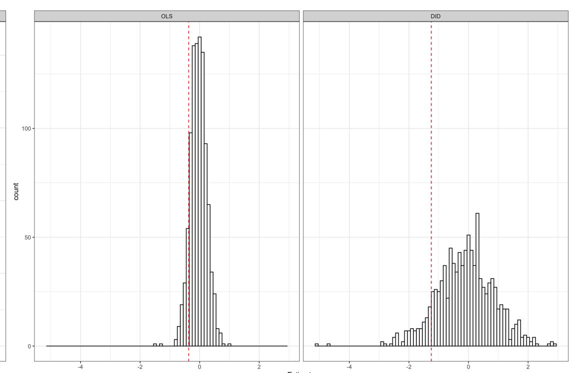
(a) Direct effects



(b) Diffusion effects at distance one



(c) Diffusion effects at distance two



(d) Dose-response relationship

Figure 21: Results of randomization inference testsfor the effects of the Nitrate Directive on nitrate concentrations in surface water

Note: Results of randomization inference tests à la Athey et al. (2018). The histograms present the distribution of the parameters of interest under the corresponding null hypothesis estimated using 1000 draws of the treatment vector. The dotted red line presents the position of the treatment effect estimate obtained using the actual data. "Direct effects" refers to the testing of the null hypothesis of absence of any effects estimated using equations (9) and (10). "Diffusion effects of order q" refers to the null hypothesis of absence of any diffusion effects at a distance lower than q estimated using equations (11) and (12) for the diffusion effects at distance one and (13) and (14) for the diffusion effects at distance two. "Dose-response relationship" refers to the null hypothesis of absence of a dose-response relationship estimated using equations (15) and (16).

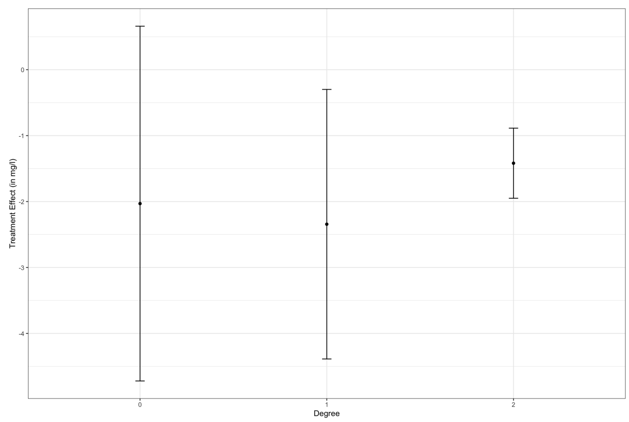
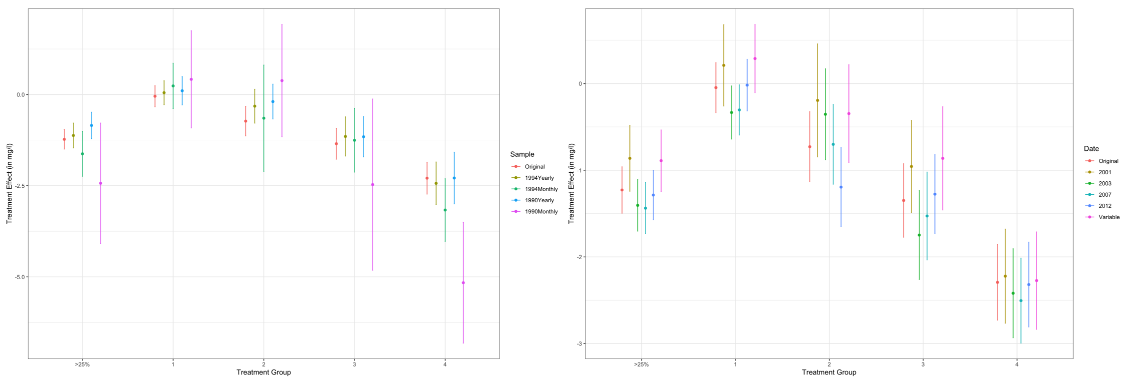


Figure 22: Impact of the Nitrate Directive as a function of the proportion of the upstream area that is covered by a vulnerable zone at distance k

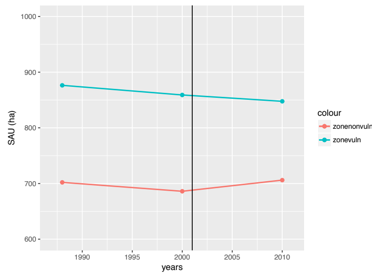
Note: Estimates of the impact of treatment intensity at several distances, obtained running equation (19) with $Q = 2$ on the sample of observations with upstream neighbors at a distance of two or more. The coefficients can be interpreted as the effect on nitrate concentrations of moving the proportion of the upstream area regulated under the directive from zero to one. Standard errors are clustered at the hydrographic zone level. Error bars are 95% confidence intervals.

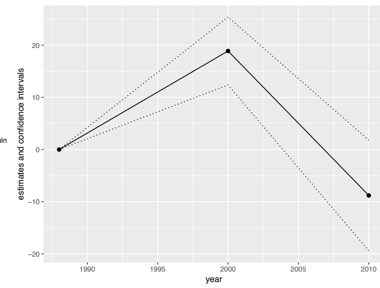


(a) Sample delimitation (b) Treatment date

Figure 23: Sensitivity of the estimates of the impact of the Nitrate Directive on nitrate concentrations to changes in sample delimitation and treatment date

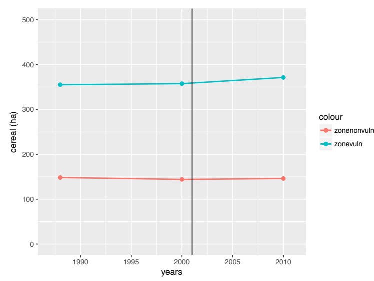
Note: Coefficients with 95% confidence intervals using standard errors clustered at the hydrographic zone level. Estimated treatment impacts on nitrate concentration (mg/L) from equation (4) with *25%-threshold treatment* definition (left) and *5-intensity treatment* definition (right). ">25%" refers to the effect of the treatment defined by the *25%-threshold treatment* definition ([0%,25%] for the control group and]25%,100%] for the treated group) while "1", "2", "3" , "4" refer to the *5-intensity treatment* ([0%,25%] for the control group and]25%,50%],]50%,75%],]75%,100%[and 100% for the treated groups). For the sample delimitation plot, "Original" refers to the sample on which we perform our main regressions (at least five observations per stations, with at least one observation before 2001), "1994Yearly" refers to the sample starting in 1994 and balanced so as to have at least one observation per year for each station, "1994Monthly" refers to the sample starting in 1994 and balanced so as to have at least one observation per month for each station, "1990Yearly" refers to the sample starting in 1990 and balanced so as to have at least one observation per year for each station and "1990Monthly" refers to the sample starting in 1990 and balanced so as to have at least one observation per month for each station. For the treatment date plot, "Original" refers to the definition of the treatment used in our main regressions (all the hydrographic zones classified as vulnerable at any time between 2001 and 2012), "2001", "2003", "2007", "2012" define as treated only the zones that are classified as vulnerable in each of those years, and "Variable" uses a time-variable definition of the treatment, where hydrographic zones are classified as treated in the years in which they are classified as vulnerable.

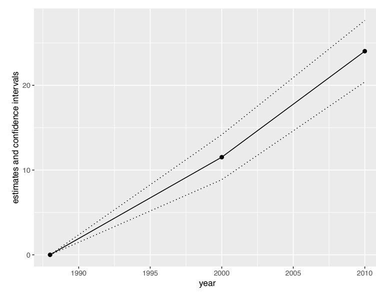




(a) Utilized Agric. Area (ha) (means)

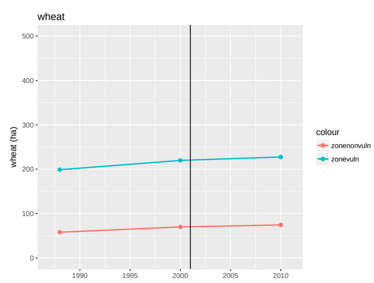
(b) Utilized Agric. Area (ha) (trends)

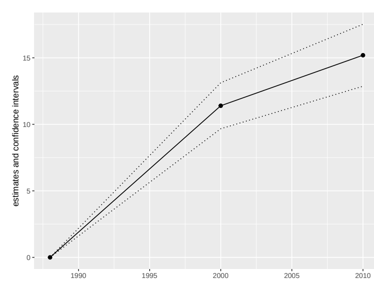




(c) Cereal Area (ha) (means)

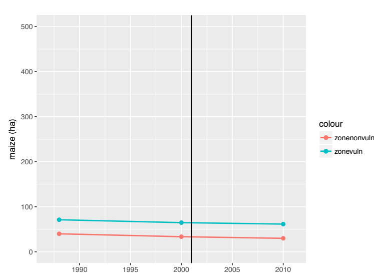
(d) Cereal Area (ha) (trends)

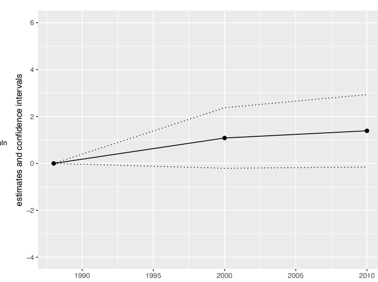




(e) Wheat Area (ha) (means)

(f) Wheat Area (ha) (trends)



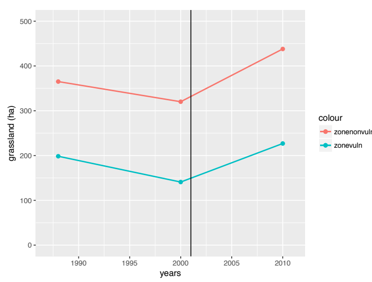


(g) Maize Area (ha) (means)

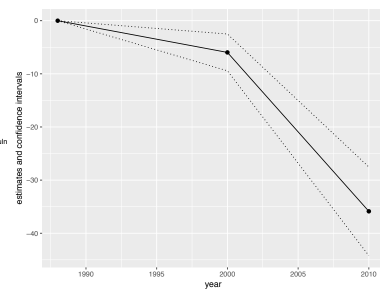
(h) Maize Area (ha) (trends)

Figure 24: Annual means by treatment group (left graphs) and trends relative to the control group (right graphs) of land use

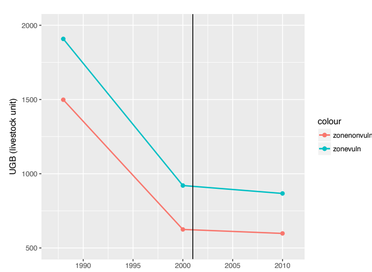
Note: On the left, trends in land use (in ha) for various crops on farms depending on whether they are located in a vulnerable zone or not. On the right, regression coefficients with year and treatment group fixed effects for the treated group with respect to the control group with 95% confidence intervals clustered at the commune level.



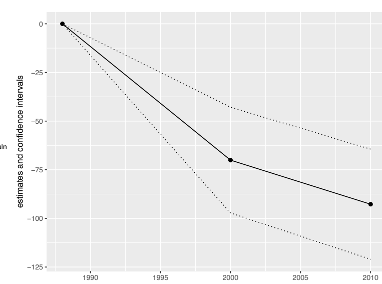
(a) Grassland Area (ha) (means)



(b) Grassland Area (ha) (means)



(c) Livestock units (means)



(d) Livestock units (trends)

Figure 25: Annual means by treatment group (left graphs) and trends relative to the control group (right graphs) of grassland area and livestock units

Note: On the left, trends in grassland area (in ha) and livestock units on farms depending on whether they are located in a vulnerable zone or not. On the right, regression coefficients with year and treatment group fixed effects for the treated group with respect to the control group with 95% confidence intervals clustered at the commune level.

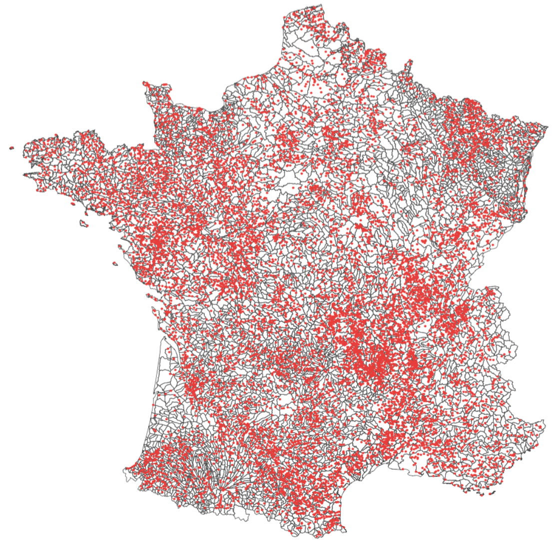
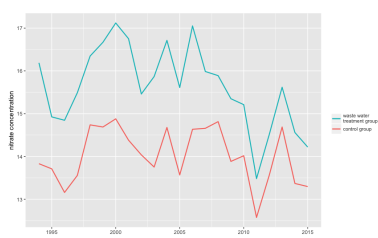
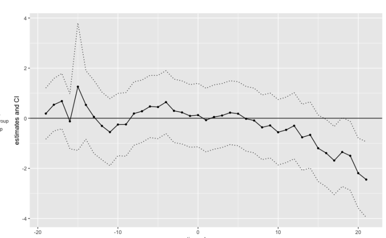


Figure 26: Wastewater treatment plants



(a) Wastewater treatment (means)



(b) Wastewater treatment (trends)

Figure 27: Annual means by treatment group (left graphs) and trends relative to the control group (right graphs) for the wastewater treatment plants

Note: On the left, trends in nitrate concentration (in mg/l) depending on whether a wastewater treatment plant is established upstream at some point in time between 1995 and 2015. On the right, regression coefficients with year, month and station fixed effects around the date of the opening of a wastewater treatment plant with 95% confidence intervals clustered at the hydrographic zone level.

Tables

Table 1: Descriptive statistics

Variables		**1993-2000**		**2005-2010**		
	unit	vulnerable	non-vulnerable	vulnerable	non-vulnerable	Sample size
Water quality						
Nitrate	mg/l	20.003	7.962	19.871	7.874	406,174
Nitrite	mg/l	0.235	0.114	0.149	0.0809	391,365
Ammonium	mg/l	0.728	0.313	0.313	0.192	408,528
Phosphorus	μg/l	0.325	0.229	0.175	0.120	372,402
Dissolved oxygen	mg/L	10.078	9.669	10.135	9.785	409,474
Chemical oxygen demand	mg/L	0.325	0.229	0.175	0.120	372,402
Chlorophyll A	μg/l	17.808	11.109	10.696	4.991	159,649
Fish	number	194	158	189	166	8,703
Fish species	number	9	8	10	8	8,703
Farming practices						
Yield (wheat)	t/ha	64.97	50.94	98.12	75.51	23,540
Nitrate-fixing crops	0/1	0.016	0.007	0.108	0.032	65,602
Grass buffer strips	0/1	0.002	0.001	0.104	0.124	51,275
N mineral fertilizers	kg/ha	122.47	123.04	133.77	131.87	65,602
P mineral fertilizers	kg/ha	51.44	56.25	30.90	36.93	65,602
Organic fertilizers	kg/ha	6.93	5.80	5.45	5.76	65,602
N output	kgN/ha	128.85	110.13	158.75	109.94	51,974
N input	kgN/ha	183.50	183.83	168.34	167.96	52,429
N balance	kgN/ha	54.68	73.56	9.58	58.03	52,429
nitrogen use efficiency	%	87.19	74.78	120.98	80.11	52,429
Accounting data						
Utilized agricultural area	ha	94.51	91.77	115.87	112.45	65,613
Production value	€/ha	633.94	430.41	756.14	478.28	65,613
Spending on fertilizers	€/ha	109.69	91.84	138.17	100.31	65,613
Spending on seeds	€/ha	84.29	74.98	120.65	86.79	65,613
Spending on pesticides	€/ha	131.37	102.92	135.71	96.42	65,613
Spending on gasoline	€/ha	46.93	44.43	72.37	66.59	65,613
Spending on analysis on crops	€/ha	106.74	77.31	118.19	84.43	65,613
Total factor productivity	index	1.67	1.47	1.85	1.53	65,613

Note: this table reports the mean of outcome variables for observations located in vulnerable areas and outside of vulnerable areas, before and after the implementation of the Nitrate Directive in France.

Table 2: Number of hydrographic zones by level of treatment intensity

Treatment Definition	**Assignment**	**Intensity**	**N**
25%-threshold treatment	control group	[0%,25%]	3128
	treated group	]25%,100%]	2980
5-intensity treatment	control group	[0%,25%]	3128
	treated group 1	]25%,50%]	477
	treated group 2	]50%,75%]	261
	treated group 3	]75%,100%[	992
	treated group 4	100%	1250

Table 3: Impact of the Nitrate Directive on the concentration of nitrates in surface water

Dependent variable:	nitrate (mg/L)		nitrate (crop season) (mg/L)	
	(1)	(2)	(3)	(4)
treated group 25%	-1.231^{***}		-1.563^{***}	
	(0.137)		(0.142)	
treated group 1		-0.049		-0.153
		(0.148)		(0.154)
treated group 2		-0.728^{***}		-0.906^{***}
		(0.207)		(0.162)
treated group 3		-1.369^{***}		-1.821^{***}
		(0.216)		(0.292)
treated group 4		-2.282^{***}		-2.728^{***}
		(0.222)		(0.243)
Controls	✓	✓	✓	✓
station FE	✓	✓	✓	✓
month FE	✓	✓	✓	✓
year×hydro district FE	✓	✓	✓	✓
R-squared	0.76	0.76	0.82	0.82
Mean Dep. Var.	15.992	15.992	17.711	17.711
Observations	406,174	406,174	198,058	198,058
Clusters	2,000	2,000	2,000	2,000

Note: This table reports the effects of the policy on nitrate concentration (in mg/L) according to the two treatment definitions. In Columns 1 and 3, the *25% threshold treatment* attributes each watershed that has a treatment intensity higher than 25% to the treated group. In Columns 2 and 4, the *5 intensity treatment* assigns each hydrographic zone to a treatment group corresponding to its treatment intensity, from 0% to 100%, by 25% increments. Columns 3 and 4 report coefficients only for a crop season (winter and spring). Regressions are run at the station level. Controls include rainfall, temperatures, quality of measurement, measurement support, portion analyzed and whether the reading is raw or has been controlled, analyzed or validated. Standard errors are clustered at the hydrographic zone level. Significance levels are $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 4: Impact of the Nitrate Directive on the concentration of nitrates in surface water by seasons and hydrographic district

Dependent variable:	nitrate	
	(1)	(2)
season *Winter*	-1.660^{***}	
	(0.197)	
season *Spring*	-0.540^{***}	
	(0.126)	
season *Summer*	-0.733^{***}	
	(0.136)	
season *Fall*	-0.711^{***}	
	(0.165)	
hydrographic district *Loire-Bretagne*		-3.900^{***}
		(0.361)
hydrographic district *Seine-Normandie*		-1.179^{***}
		(0.401)
hydrographic district *Medit-Rhône*		-0.639^{*}
		(0.378)
hydrographic district *Rhin-Meuse*		-0.560^{*}
		(0.314)
hydrographic district *Adour-Garonne*		0.443^{*}
		(0.256)
Controls	✓	✓
station FE	✓	✓
month FE	✓	✓
year×hydro district FE	✓	✓
R-squared	0.77	0.76
Mean Dep. Var.	15.992	15.992
Observations	406,174	406,174
Clusters	2,000	2,000

Note: This table reports the effects of the policy on nitrate concentration (in mg/L). Columns 1 presents the effects according to each season and Column 2 relative to each hydrographic districts. Controls include rainfall, temperatures, quality of measurement, measurement support, portion analyzed and whether the reading is raw or has been controlled, analyzed or validated. Standard errors are clustered at the hydrographic zone level. Significance levels are $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 5: Impacts of the Nitrate Directive on physico-chemical indicators other than nitrates

Dependent variable:	nitrites	ammonium	phosphorus	dissolved oxygen	COD
Unit:	(mg/l)	(mg/l)	(μg/l)	(mg/l)	(mg/l)
	(1)	(2)	(3)	(4)	(5)
treated group 25%	-0.032^{***}	-0.119^{**}	-0.0268^{**}	0.055^{*}	0.189
	(0.006)	(0.055)	(0.0116)	(0.037)	(0.505)
Controls	✓	✓	✓	✓	✓
station FE	✓	✓	✓	✓	✓
month FE	✓	✓	✓	✓	✓
year×hydro region FE	✓	✓	✓	✓	✓
R-squared	0.38	0.48	0.31	0.35	0.44
Mean Dep. Var	0.147	0.365	0.1951	9.874	19.123
Observations	406,174	408,528	372,402	409,474	209,802

Note: This table reports the effects of the policy on nitrites (mg/l), ammonium (mg/l), phosphorus (μg/l), dissolved oxygen (mg/l) and chemical oxygen demand (COD) (mg/l) according to the *25% threshold treatment* definition. Regressions are run at the station level. Controls include rainfall, temperatures, quality of measurement, measurement support, portion analyzed and whether the reading is raw or has been controlled, analyzed or validated. Standard errors are clustered at the hydrographic zone level. Significance levels are $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 6: Impacts of the Nitrate Directive on eutrophication and biodiversity

	Eutrophication		**Biodiversity**	
Dependent variable:	chlorophyll A	chlorophyll A (spring & summer)	stock of fish (number)	fish species (number)
	(1)	(2)	(3)	(4)
treated group 25%	-2.699^{***}	-3.002^{***}	69.84^{***}	0.918^{***}
	(0.717)	(0.772)	(11.79)	(0.224)
Controls	✓	✓	✓	✓
station FE	✓	✓	✓	✓
month FE	✓	✓	✓	✓
year FE	✓	✓	✓	✓
R-squared	0.29	0.31	0.42	0.80
Mean dep. var.	11.31	12.91	176.93	9.112
Observations	159,649	112,918	8,703	8,703

Note: This table reports the effects of the policy on chlorophyll A (μg/L) and the number of fish according to the *25% threshold treatment* definition. Regressions are run at the station level. Controls for chlorophyll A include rainfall, temperatures, quality of measurement, measurement support, portion analyzed and whether the reading is raw or has been controlled, analyzed or validated. Controls for the number of fish and the number of fish species index include rainfall and temperatures. Standard errors are clustered at the watershed level. Significance levels are $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 7: Impacts of the Nitrate Directive on farming practices aimed at reducing the transfer of pollutants

Dependent variable:	nitrogen-fixing crop (% of plots) (1)	grass buffer strip (% of plots) (2)
vulnerable areas	0.061^{***} (0.005)	-0.010 (0.014)
Weights	✓	✓
year FE	✓	✓
departement FE	✓	✓
Mean Dep. Var.	0.050	0.036
R-squared	0.08	0.09
Observations	65,602	51,275

Note: This table reports the effects of the policy on plots under nitrogen-fixing intermediate crops and grass buffer strips. Regressions are run at the commune level. Standard errors are clustered at the plot level. Significance levels are $^{***}p < 0.01,^{**}p < 0.05,\ ^{*}p < 0.10$.

Table 8: Impacts of the Nitrate Directive on practices aimed at increasing the effectiveness of nitrogen management

Dependent variable:	N estimated (% of plots) (1)	N adjusted (after winter) (% of plots) (2)
Vulnerable areas	0.064^{***} (0.014)	0.102^{***} (0.010)
Controls	✓	✓
Weights	✓	✓
year FE	✓	✓
departement FE	✓	✓
R-squared	0.13	0.14
Mean Dep. Var.	0.314	0.142
Observations	54,455	61,714

Note: This table reports the effects of the policy on plots for which (column 1) farmers have assessed the amounts of nitrogen remaining in the soil, and (column 2) farmers have adjusted the amounts of nitrogen applied to lands, depending on estimated nitrogen in the soil after winter. Controls include type of crops and utilized agricultural area. Regressions are run at the commune level. Standard errors are clustered at the commune level. Significance levels are $^{***}p < 0.01,^{**}p < 0.05,\ ^{*}p < 0.10$.

Table 9: Impacts of the Nitrate Directive on fertilization and nitrogen use efficiency

	Amount of fertilizers			**N Indicators**			
Dependent variable:	N (kgN/ha) (1)	P (kgP/ha) (2)	manure (kgN/ha) (3)	N input (kgN/ha) (4)	N output (kgN/ha) (5)	NUE (%) (6)	N balance (kgN/ha) (7)
Vulnerable areas	-2.764	-1.454	-1.435^{**}	0.882	9.614^{***}	16.279^{***}	-9.580^{***}
	(1.700)	(1.056)	(0.662)	(2.297)	(2.410)	(3.884)	(3.349)
Controls	✓	✓	✓	✓	✓	✓	✓
Weights	✓	✓	✓	✓	✓	✓	✓
year FE	✓	✓	✓	✓	✓	✓	✓
departement FE	✓	✓	✓	✓	✓	✓	✓
R-squared	0.20	0.18	0.01	0.06	0.15	0.04	0.12
W. Mean Dep. Var.	126.060	41.331	6.618	175.371	136.076	97.834	39.101
Observations	65,602	65,602	65,602	52,429	51,974	52,429	52,429

Note: This table reports the effects of the policy on mineral and organic fertilizers applied on land, i.e. nitrogen N, phosphorus P and manure, and on indicators measuring agricultural performance in terms of nitrogen, i.e. nitrogen use efficiency, nitrogen balance and nitrogen output. Controls include type of crops and utilized agricultural area. Regressions are run at the commune level. Standard errors are clustered at the commune level. Significance levels are $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 10: Impacts of the Nitrate Directive on farmers' profits

Dependent variable: vulnerable areas	Output (€/ha) (1)	- Fertilizers (€/ha) (2)	- Seeds (€/ha) (3)	- Pesticides (€/ha) (4)	- Fuel (€/ha) (5)	- Soil analysis (€/ha) (6)
All farmers	18^{***}	13^{**}	12^{**}	9^{*}	8	6
	(6)	(6)	(6)	(5)	(3)	(6)
Crop growers	29^{**}	23^{*}	24^{*}	18	20^{*}	13
	(12)	(12)	(12)	(12)	(11)	(12)
year FE	✓	✓	✓	✓	✓	✓
Farm FE	✓	✓	✓	✓	✓	✓

Note: This table reports the effects of the Nitrate Directive on components of farmers' profits per hectare: value of output (column (1)), value of output minus spending on fertilizers (column (2)), value of output minus spending on fertilizers and seeds (column (3)), value of output minus spending on fertilizers, seeds and pesticides (column (4)), value of output minus spending on fertilizers, seeds, pesticides and fuel (column (5)), and value of output minus spending on fertilizers, seeds, pesticides, fuel and soil analysis (column (6)). Regressions are run at the farm level with farm and year fixed effects. Standard errors are clustered at the commune level. Significance levels are $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 11: Impacts of the Nitrate Directive on farmers' total factor productivity

	TFP (1)	TFP (2)	TFP (3)
Vulnerable areas	0.0524^{**}	0.0476^{**}	0.0417^{*}
	(0.0225)	(0.0215)	(0.0215)
Farm FE	✓	✓	✓
year FE	✓		
region×year FE		✓	
region×year×OTEX FE			✓
Mean Dep. Var.	0.65	0.65	0.65
Observations	45123	45123	45123

Note: This table reports the effects of the Nitrate Directive on farmers' total factor productivity. Regressions are run at the farm level with farm fixed effects and year fixed effects (column 1), region×year fixed effects (column 2) and region×year×OTEX, where OTEX is the technical orientation of the farm computed from its main sources of revenue (cereals, cattle growing, miced farming, etc.). Standard errors are clustered at the commune level. Significance levels are $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 12: Impacts of the Nitrate Directive on the Variance of the Nitrogen Mineral Fertilizers Applied on Plots

Dependent variable:	Variance(N Fertilizers) $(\text{Nkg/ha/year})^2$
vulnerable areas	376.30^{**} (155.02)
year FE	✓
department FE	✓
Mean Dep. Var.	5,195
R-squared	0.09
Observations	65,602

Note: This table reports the effects of the policy on the variance of the nitrogen mineral fertilizers in vulnerable areas relative to non-vulnerable areas, with Variance(N fertilizers) = (Amount of N fertilizers at the plot level - National mean of N fertilizers applied on plots)^2. Regressions are run at the plot level. Standard errors are clustered at the commune level. Significance levels are $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 13: Impacts of the Nitrate Directive on nitrate concentration in surface water using alternative estimators

Dependent variable:			**nitrate** (mg/L)		
	CFRT	DID	KS	CFRT	DID
	(1)	(2)	(3)	(4)	(5)
Treatment dummy	-1.231^{***}	-1.141^{***}	-1.027^{***}		
	(0.137)	(0.123)	(0.324)		
treated group 1				-0.049	0.088
				(0.148)	(0.243)
treated group 2				-0.728^{***}	-0.171
				(0.207)	(0.206)
treated group 3				-1.369^{***}	-0.970^{***}
				(0.216)	(0.234)
treated group 4				-2.282^{***}	-1.595^{***}
				(0.222)	(0.163)
Controls	✓	✓	✓	✓	✓
station FE	✓	✓	✓	✓	✓
month FE	✓	✓	✓	✓	✓
year×hydro district FE	✓	✓		✓	✓
year×pair FE			✓		
year×hydro district×downstream FE			✓		
R-squared	0.760	0.760	0.796	0.760	0.760
Mean Dep. Var.	15.992	15.992	12.41	15.992	15.992
Observations	406,174	406,174	375,153	406,174	406,174

Note: This table reports the effects of the Nitrate Directive on nitrates concentrations in surface water (in mg/l) using several estimators. "CFRT" refers to the approach delineated in equation (4) using treatment intensity. "DID" refers to the classical DID approach ignoring diffusion effects, as delineated in equation (5). "KS" refers to the geographical discontinuity design estimator of Keiser and Shapiro (2017) presented in equation 6. Columns 1, 2 and 3 use the *25% threshold treatment* definition while columns 4 and 5 use the *5-intensity treatment* which assigns each watershed into a treatment group corresponding to its treatment intensity from 0% to 100%, by 25% increments. Regressions are run at the station level. Controls include rainfall, temperatures, quality of measurement, measurement support, portion analyzed and whether the reading is raw or has been controlled, analyzed or validated. Standard errors are clustered at the hydrographic zone level. Significance levels are $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 14: Impact of the Nitrate Directive on water quality with the balanced panel

Dependent variable:	nitrates (mg/L)		nitrites (mg/L)	ammonium (mg/L)	phosphorus (μg/L)	dissolved oxygen (mg/L)	DCO (mg/L)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
treated group 25%	-1.112^{***}		-0.039^{***}	-0.161^{*}	-0.028^{*}	0.080^{**}	-1.559^{*}
	(0.178)		(0.007)	(0.086)	(0.017)	(0.037)	(0.861)
treated group 1		0.012					
		(0.197)					
treated group 2		-0.205					
		(0.250)					
treated group 3		-1.275^{***}					
		(0.287)					
treated group 4		-2.251^{***}					
		(0.304)					
Controls	✓	✓	✓	✓	✓	✓	✓
station FE	✓	✓	✓	✓	✓	✓	✓
month FE	✓	✓	✓	✓	✓	✓	✓
year×hydro district FE	✓	✓	✓	✓	✓	✓	✓
R-squared	0.73	0.74	0.41	0.49	0.28	0.44	0.34
Mean Dep. Var.	15.872	15.872	0.166	0.453	0.216	9.903	18.609
Observations	224,236	224,236	210,490	225,832	186,757	203,452	76,780
Clusters	921	921	921	921	921	921	921

Note: This table reports the effects of the policy on nitrate concentrations and other physico-chemical parameters including land use change as control variables (utilized agricultural area, cereal surface, wheat surface, maize surface and grassland surface). Regressions are run at the station level. Controls include quality of measurement, measurement support, portion analyzed and whether the reading is raw or has been controlled, analyzed or validated, livestock, utilized agricultural surface, surface in cereals, wheat, maize and grassland and climate control (monthly rainfall and temperatures). Standard errors are clustered at the hydrographic zone level. Significance levels are $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.10$.

Table 15: Impact of the Nitrate Directive on eutrophication and biodiversity with the balanced panel)

Dependent variable:	chlorophyll A (μg/L)		fish (number)		fish species (number)	
	(1)	(2)	(3)	(4)	(5)	(6)
treated group 25%	-2.868^{***}	-2.493^{**}	122.500^{***}	39.862	0.918^{***}	0.400
	(0.956)	(1.058)	(31.330)	(36.316)	(0.224)	(0.233)
Controls	✓	✓	✓	✓	✓	✓
station FE	✓	✓	✓	✓	✓	✓
month FE	✓	✓	✓	✓	✓	✓
year FE		✓		✓		✓
year×hydro district FE	✓		✓		✓	
R-squared	0.27	0.27	0.42	0.42	0.80	0.81
Mean Dep. Var.	13.207	13.207	179.702	179.702	9.112	9.112
Observations	73,350	73,350	1,471	1,471	8,703	8,703
Cluster	424	424	62	62	62	62

Note: This table reports the effects of the policy on chlorophyll A and other biological parameters. Regressions are run at the station level. Controls for chlorophyll A include quality of measurement, measurement support, portion analyzed and whether the reading is raw or has been controlled, analyzed or validated and climate control for both chlorophyll A and fish outcomes (monthly rainfall and temperatures). Standard errors are clustered at the hydrographic zone level. Significance levels are $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.10$.

Table 16: Impact of the Nitrate Directive on land use and livestock units

Dependent variable:	utilized agricultural area (ha) (1)	livestock (livestock unit) (2)	cereal (ha) (3)	wheat (ha) (4)	maize (ha) (5)	grassland (ha) (6)
vulnerable area	-18.223^{***}	-57.783^{***}	18.279^{***}	9.509^{***}	0.850	-32.895^{***}
	(4.344)	(8.289)	(1.325)	(0.870)	(0.545)	(4.053)
Controls	✓	✓	✓	✓	✓	✓
year FE	✓	✓	✓	✓	✓	✓
departement FE	✓	✓	✓	✓	✓	✓
R-squared	0.51	0.55	0.39	0.38	0.35	0.35
Cluster	35,241	35,241	35,241	35,241	35,241	35,241
Mean Dep. Var.	781.694	1,076.138	256.548	143.230	50.541	279.026
Observations	104,535	104,535	104,535	104,535	104,535	104,535

Note: This table reports the effects of the policy on land use and livestock units. Regressions are run at the station level. Control include the number of farms per communes. Standard errors are clustered at the commune level. Significance levels are $^{***}p < 0.01$,$^{**}p < 0.05$, $^{*}p < 0.10$.

Table 17: Impact of the Nitrate Directive on water quality controlling for land use

Dependent variable:	nitrates (mg/L) (1)	(2)	nitrites (mg/L) (3)	ammonium (mg/L) (4)	phosphorus (μg/L) (5)	dissolved oxygen (mg/L) (6)	DCO (mg/L) (7)
treated group 25%	-1.248^{***}		-0.030^{***}	-0.133^{**}	-0.026^{**}	0.062^{*}	-1.769^{*}
	(0.136)		(0.005)	(0.058)	(0.012)	(0.032)	(0.919)
treated group 1		-0.211					
		(0.151)					
treated group 2		-0.771^{***}					
		(0.222)					
treated group 3		-1.439^{***}					
		(0.212)					
treated group 4		-2.110^{***}					
		(0.216)					
Surface water controls	✓	✓	✓	✓	✓	✓	✓
Climate controls	✓	✓	✓	✓	✓	✓	✓
Land use change	✓	✓	✓	✓	✓	✓	✓
Livestock	✓	✓	✓	✓	✓	✓	✓
station FE	✓	✓	✓	✓	✓	✓	✓
month FE	✓	✓	✓	✓	✓	✓	✓
year×hydro district FE	✓	✓	✓	✓	✓	✓	✓
R-squared	0.76	0.76	0.38	0.44	0.30	0.34	0.36
Cluster	280	280	280	280	280	280	280
Mean Dep. Var.	15.992	15.992	0.147	0.365	0.1951	9.903	18.609
Observations	406,174	406,174	391,365	408,528	372,402	409,474	76,780

Note: This table reports the effects of the policy on nitrate concentrations and other physico-chemical parameters including land use change as control variables (utilized agricultural area, and cereal, wheat, maize and grassland areas). Regressions are run at the station level. Controls include quality of measurement, measurement support, portion analyzed and whether the reading is raw or has been controlled, analyzed or validated, livestock, utilized agricultural area, and cereal, wheat, maize and grassland areas and climate control (monthly rainfall and temperatures). Standard errors are clustered at the hydrographic zone level. Significance levels are $^{***}p < 0.01$,$^{**}p < 0.05$, $^{*}p < 0.10$.

Table 18: Impact of the Nitrate Directive on eutrophication and biodiversity controlling for land use

Dependent variable:	chlorophyll A (μg/L)		fish (number)		fish species (number)	
	(1)	(2)	(3)	(4)	(5)	(6)
treated group 25%	-3.260^{***}	-2.399^{***}	41.012^{***}	69.129^{***}	0.300	0.905^{***}
	(0.776)	(0.705)	(11.618)	(11.933)	(0.232)	(0.235)
Surface water controls	✓	✓				
Climate controls	✓	✓	✓	✓	✓	✓
Land use change	✓	✓	✓	✓	✓	✓
Livestock	✓	✓	✓	✓	✓	✓
station FE	✓	✓	✓	✓	✓	✓
month FE	✓	✓	✓	✓	✓	✓
year FE		✓		✓		✓
year×hydro district FE	✓		✓		✓	
R-squared	0.29	0.28	0.50	0.43	0.81	0.80
Cluster	280	280	280	280	280	280
Mean Dep. Var.	11.311	11.311	176.9	176.9	9.1	9.1
Observations	154,853	154,853	8,703	8,703	8,703	8,703

Note: This table reports the effects of the policy on chlorophyll A and other biological parameters. Regressions are run at the station level. Controls for chlorophyll A include quality of measurement, measurement support, portion analyzed and whether the reading is raw or has been controlled, analyzed or validated, livestock, utilized agricultural area, and cereal, wheat, maize and grassland areas and climate control (monthly rainfall and temperatures). Standard errors are clustered at the hydrographic zone level. Significance levels are $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 19: Impact of the Nitrate Directive on water quality controlling for wastewater treatment plants

Dependent variable:	nitrate		nitrites	ammonium	phosphorus	dissolved oxygen	DCO
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
treated group 25%	-1.241^{***}		-0.0321^{***}	-0.118^{**}	-0.0256^{**}	0.077^{**}	-1.551^{*}
	(0.138)		(0.0057)	(0.055)	(0.0115)	(0.037)	(0.869)
treated group 1		-0.286^{**}					
		(0.136)					
treated group 2		-0.202					
		(0.152)					
treated group 3		-0.895^{***}					
		(0.206)					
treated group 4		-1.546^{***}					
		(0.221)					
treated group 5		-2.442^{***}					
		(0.225)					
Surface water controls	✓	✓	✓	✓	✓	✓	✓
Wastewater treatment	✓	✓	✓	✓	✓	✓	✓
station FE	✓	✓	✓	✓	✓	✓	✓
month FE	✓	✓	✓	✓	✓	✓	✓
year×hydro district FE	✓	✓	✓	✓	✓	✓	✓
R-squared	0.76	0.76	0.38	0.48	0.31	0.44	0.36
Mean Dep. Var.	15.992	15.992	0.147	0.365	0.1951	9.903	18.609
Observations	406,174	406,174	391,365	408,528	372,402	203,402	76,780

Note: This table reports the effects of the policy on nitrate concentration. Regressions are run at the station level. Controls include quality of measurement, measurement support, portion analyzed and whether the reading is raw or has been controlled, analyzed or validated. Standard errors are clustered at the hydrographic zone level. Significance levels are $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.