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Predicting Farms' Noncompliance with Regulations on Nitrate Pollution

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Abstract: Despite ongoing efforts by regulatory authorities, there is significant noncompliance with the EU Nitrates Directive among farms in Ireland. Nutrient pollution harms water quality and ecosystems, and farms are subject to fines for noncompliance. This paper examines reasons for noncompliance and develops methods to predict which farms have the highest probability of being in breach of the Nitrates Regulations. We estimate econometric models of noncompliance using rich administrative data on farm and farmer characteristics collected by Ireland's Department of Agriculture. We identify significant relationships between farm characteristics and the odds of a farm exceeding regulatory limits. We also find that econometric models can predict exceedances more accurately than a regulatory rule-of-thumb that flags farms with nitrates levels above a set threshold in the previous year. This approach illustrates the potential benefits of using statistical analysis of administrative data to assist regulatory enforcement when behavioural factors are involved.

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Non-Technical Summary

Every year approximately 2,000 farms in Ireland violate the EU Nitrates Regulations. Although small when expressed as a proportion of more than 130,000 Irish farms, the rate of noncompliance has remained fairly constant in recent years, with knock-on effects for water quality. In this paper, we present the results of a large-scale statistical analysis of the characteristics of farms and farmers that exceed the basic regulatory limit of 170 Kg of nitrogen per hectare (NPH). (The analysis excludes farms that successfully apply for a derogation that increases this limit to 250 Kg NPH, provided they meet additional conditions).

We were granted access to relevant administrative datasets held by the Department of Agriculture, Food and the Marine (DAFM) for the period 2006-2015. These were cleaned and combined into a master dataset containing more than 1,250,000 individual records. The construction of such a large dataset allowed the application of sensitive statistical techniques, which were used to relate the characteristics of farms and farmers to the likelihood of noncompliance with the regulations.

The primary purpose of the analysis was to build models that are able to predict which farms are most at risk of noncompliance. On an ongoing basis such models can be updated with the latest data and used to identify farms that are most likely to violate the regulations, with a view to targeting interventions accordingly. A secondary aim of this research was to give insights into the types of farms and farmers most likely not to comply. Although the data did not contain information about individual farmers' behaviours and attitudes, the associations uncovered by the models nevertheless permit some insights. Statistical models were applied both to the data for individual years and to the data for all the years combined. The results from both types of models were similar.

We found that the higher the level of NPH in previous years, the higher the risk of noncompliance. While at one level this is not surprising, the steady increase in the likelihood of noncompliance (rather than a threshold level above which farms are at substantially greater risk) implies that many violations are not due to small changes in behaviour, but instead reflect substantial changes to business practice from year to year. Farms with smaller land holdings are also more likely to violate the regulations. This may be because small farms face lower penalties, on average, and require less substantial changes in stocking rates to break regulatory limits. Interestingly, older farmers are less likely to be in breach. Combined with the other findings, this is consistent with the possibility that regulatory violations are most likely when a farm business undergoes change, perhaps because of a new business model, expanded production, or the transaction of land. Noncompliance was also variable across different counties. A detailed pattern emerged from the models, which is mapped in the main body of the paper and the Annex.

We compared the predictive performance of the statistical models against a rule-of-thumb used by DAFM, which is to target farms above 150 Kg NPH. The models are able to identify those farms that have a higher probability of noncompliance more accurately than this rule. By updating the models to make use of the most recently available data, it should be possible to exploit them in coming years to identify those farms that are at greatest risk of noncompliance and to target and test interventions accordingly.

1. Introduction

Regulatory measures form an important component of the policy toolkit used to protect and enhance the environment. Along with publicly-provided information, provision of public goods and economic instruments such as taxes and subsidies, regulatory restrictions can help correct market failures and improve societal welfare. While policymakers give considerable attention to the design, targeting and stringency of regulations, effective implementation and enforcement is vital too. Ideally, regulators should try to maximise compliance with regulations while economising on the administrative and policy cost. This process can benefit from better understanding of the behavioural responses of those being regulated.

The present paper demonstrates how statistical analysis of administrative data can be used to learn more about compliance behaviour, in this case the behaviour of farmers. We use data from Ireland’s DAFM, Food and the Marine (hereafter DAFM). Our focus is on identifying the characteristics of farmers or their farms that can help to predict noncompliance with regulations intended to limit emissions of nitrates. Knowing more about these characteristics can help regulators to target programmes designed to increase compliance, thereby assisting efforts to protect the natural environment and encouraging a minority of farmers to avoid unnecessary penalties. A further objective is to identify farms most at risk of noncompliance in order to inform the selection of suitable sample groups for trials of behavioural interventions designed to increase compliance (see Lunn, 2018, *forthcoming*).

We hypothesise, and find, that noncompliance is more likely among smaller farms and those farms that were closer to breaking the regulations the previous year. Additionally, violation is more likely among farms that exceeded regulatory limits in the past, highlighting the presence of repeat offenders despite penalties. Noncompliance is also much more likely among younger farmers than older farmers. Lastly, we show that the statistical models behind these results predict violations more accurately than a standard rule-of-thumb employed by DAFM, which flags farms with nitrates levels for the previous year above a threshold of 150 Kg per hectare.

The remainder of the paper is structured as follows: The next section provides necessary background information on the Nitrates Regulations as well as considering previous relevant literature on agricultural regulatory compliance. Section 3 describes the data used, while the methods used to answer our research questions are discussed in Section 4. Results are presented in Section 5, before a conclusion and discussion of potential future research is given in Section 6.

2. Background and previous research

This section outlines the regulatory background and discusses some previous research into farmers’ compliance with environmental regulations.

2.1 Nitrates regulation in Ireland

The European Nitrates Directive (91/676/EEC) – *Council Directive of 12 December 1991 concerning the protection of waters against pollution caused by nitrates from agricultural sources* – was adopted in 1991. It has the objective of limiting nitrate concentration in ground and surface water. Ondersteijn et al. (2002) detail many negative consequences caused by nutrient pollution from agriculture including eutrophication of surface and marine waters which can lead to explosive algae growth, as well as potential health hazards from nitrogen exposure, such as 'blue-baby syndrome' and stomach cancer.

Compliance with the Nitrates Regulations is one of the Statutory Management Requirements under the Single Payment Scheme, introduced in the Common Agricultural Policy (CAP) reforms of 2003 which attempted to harmonise agriculture regulations across EU Member States.[1] The reforms made clear that each payment of the CAP would be conditional on a farm's cross compliance of a variety of agricultural regulations. Failure to comply with the regulations puts a farm's Single Payment at risk with penalty deductions in operation.

Ireland's first Nitrates Action Programme (NAP) under the Nitrates Directive came into operation in 2006. The current regulations in Ireland are set out in the European Communities (Good Agricultural Practice for Protection of Waters) Regulations, 2014, which we describe as the 'Nitrates Regulations'.[2] Under the Nitrates Regulations, farmers are obliged to ensure that the total amount of Nitrogen (N) from livestock manure does not exceed 170 Kg of N per hectare per year (hereafter NPH). This limit is equivalent to two dairy cows per hectare. The NPH figure for each farm in a given year is arrived at by dividing the figure for the total kilograms of nitrogen produced on the farm, obtained from the Animal Identification and Movement (AIM) System, by the farm's eligible area under the Basic Payment Scheme.[3]

If a farm is deemed to have violated the regulation in a particular year, it receives a statement early in the next following year.[4] Appeals can be made and farmers can submit further documentation explaining the reasons for their breach, but if the farm is still deemed to be over the limit following any appeal, a penalty letter is issued. Penalties are higher for repeated breaches within three calendar years. On a first repetition, the initial sanction is multiplied by a factor of three. For further reoccurrences, the previous percentage sanction is multiplied by three, up to a maximum sanction of 15%. Repeated breaches after this can lead to higher sanctions up to the loss of an entire year's Single Farm Payment under the Basic Payment Scheme. The national average value for a Single Farm Payment was around €9,414 in 2018.[5]

Farmers can apply for a "Nitrates Derogation" which allows them to apply greater amounts of livestock manure per year, up to a maximum of 250 Kg of NPH subject to some additional conditions being met.[6] Eligible grassland farmers have to make an annual application to avail of this derogation. DAFM provides annual nitrogen and phosphorus statements online as a service to all farmers registered.[7] Interim nitrogen and phosphorus statements have also recently become available,

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[1] There is variation in how the Nitrates Directive operates in each of the member states.

[2] Ireland's 4th Nitrates Action Programme was introduced in early 2018, effective for 2018-2021. However, this paper considers the time period before the 4th NAP.

[3] This information has been taken from a leaflet informing farmers how to avoid breaching the regulation. https://www.agriculture.gov.ie/media/migration/ruralenvironment/environment/nitrates/InfoLeafletNitrates220915.pdf

[4] At that stage, submission of export forms or rental agreements cannot be accepted as the deadline for submission would have been the 31st December of the year in question.

[5] Author's calculation from data taken from DAFM in February 2018 https://www.agriculture.gov.ie/schemepaymentsupdate/

[6] For example, farms that have more than 70% of their total land in use as grassland.

[7] This can be accessed at www.agfood.ie. It is a record of annual N and P produced by cattle only, so any other livestock N and P figures have to be calculated and added on by the farmers themselves.

covering the periods January to August. These statements can be of benefit to farmers, especially if stock numbers have increased in the past year. They are designed to assist in deciding whether or not to take any action before the end of the year to stay within the 170/250 Kg NPH limit.

2.2 Previous research

As far as we know, this is the first paper to use farm-level administrative data to investigate the relationship between farm characteristics and noncompliance with a specific agricultural regulation. This is made possible by the availability of data that is sometimes not retained by regulators or is heavily restricted in its use for research purposes. Lippert et al. (2014) is the closest research to our own. They model noncompliance with organic standards drawing on the economics of crime approach (Becker, 1974) to develop and test several hypotheses regarding the likelihood that a farmer fails to comply with organic standards. We make use of the results of this study to guide our own hypotheses and tests (see below). Jongeneel et al. (2007) estimate the degree and cost of compliance with a set of Statutory Management Requirements (SMRs) associated with CAP in a number of European countries. They find that the degree of compliance is generally high across the SMRs with two exceptions – the Nitrates Directive and the Identification and Registration requirements, where there have been rates of noncompliance up to 30% for both. The authors attribute the noncompliance rates for the Nitrates Directive to delays in the adjustment of national legislation to meet stricter EU standards, rather than to compliance with and enforcement of national legislation. EU standards add stringency to regulation at the farm level and provide less leeway on compliance. The costs of noncompliance with the Nitrates Directive can be as high as several thousand Euros for some offending farms. Specific to the Nitrates Regulations, Kuik (2006) reviews a number of ex-ante studies that estimate the costs to farmers of the implementation of the Nitrates Directive. He finds a range of costs per hectare from €6 to €236 across different member states and different sectors. However, this paper only looks at the costs and benefits to the producer (i.e. the farmer), overlooking the wider impacts of such regulation.

Herzfeld & Jongeneel (2008) review the economic theories of compliance with respect to agriculture and argue for revising models of compliance to incorporate findings from the psychological and behavioural literature, departing from the traditional view of compliance as the outcome of a cost-benefit decision. For example, it can be argued that peer group effects and institutional quality are useful tools for understanding compliance behaviour. The authors suggest that further empirical analysis is needed to discover appropriate variables to include when investigating compliance. Our paper seeks to do this.

Attitudes towards regulations and the trust in regulatory institutions can influence compliance behaviour. Buckley (2012) investigates Irish farmer opinions towards the Nitrates Directive Regulations and NAP. He finds four main groupings of opinions based on farmers in the Catchments Area Programme in Ireland. Two, identified as “Constrained Practitioners and “Concerned Productionists”, view the regulations as interference in farm management and are generally sceptical regarding environmental benefits. Two other groups, “Concerned Practitioners” and “Benefit Accepters” react favourably towards the regulations and show an appreciation of the benefits of improved water quality. The identification of the last two groups of farmers was novel and possibly hints at progress in farmers’ attitudes towards nutrient management. However, Irish farmers across all groups apart from the “Concerned Practitioners” in the Buckley (2012) study are averse to a nitrates cross compliance inspection.[8]

[8] Young (2010a) noted that just over one fifth of farmers in Ireland who received an on-farm inspection in 2009 were found to have some level of noncompliance.

Using a choice experiment, Buckley et al. (2012) found little willingness of Irish farmers to install riparian buffer zones on their farms. In a hypothetical choice offering monetary compensation, over half of the farmers surveyed in the Catchment Areas Programme nevertheless indicated a negative preference towards buffer zones due to loss of land and nuisance concerns. Furthermore, Buckley et al. (2016) report that since NAP came into force in Ireland in 2006, mean nitrogen balances have fallen by 25.1 Kg NPH and nitrogen use efficiencies have improved.

In summary, previous literature reveals that noncompliance with the Nitrates Directive is a significant problem across the EU, including in Ireland. Most studies reviewed above have considered general reasons for noncompliance such as attitudes to regulators, some recording substantial scepticism towards environmental benefits, albeit that attitudes may be changing. Lippert et al. (2014) is useful for selecting farm characteristics that may be associated with noncompliance of an agricultural regulation, which helps to inform our statistical models in Section 2.2.

3. Data

We use ten years of administrative data provided by the Nitrates Section of DAFM, encompassing the period 2006-2015. The Department collects a rich farm-level data in relation to livestock, land holding, and the import and export of fertilisers, among other variables. There is a full 100% administrative check on the livestock manure nitrogen limit. All farms are provided with unique alphanumeric herd identification numbers as required in the Cattle Identification and Registration Directive S.I. No. 276/1999 - *European Communities (Identification and Registration of Bovine Animals) Regulations, 1999*.[9] These herd ID numbers enabled the matching of different datasets from separate administrative files. We constructed a master, farm-level panel data set with a total of 1,287,728 observations. The panel is unbalanced, as not all farms are covered by complete data over the ten year period. There were around 144,079 farms in operation in Ireland as of 2015.

3.1 Dependent variable: Violation

Our principal dependent variable indicates violations of the regulatory limits. The variable takes the value 1 if a farm exceeded the regulatory limit of 170 Kg NPH in a given year and 0 otherwise. We classify exceedance of this regulatory limit as a violation,[10] excluding those farms with a valid derogation. Table 1 displays the number of farms that breached the regulation each year.

[9] http://www.irishstatutebook.ie/eli/1999/si/276/made/en/print

[10] In practice, DAFM allows for human error in the measurement or calculation of the NPH figure, so a limit of 171.7 NPH is the exact cut-off point for violations. We use the 171.7 figure in the creation of the dependent variable.

Table 1: Nitrates Regulation Violations by year (excluding farms with derogations)

	Clear	Violation	Total	Percentage in violation
2006	114,233	8,432	122,665	6.87
2007	117,627	3,113	120,740	2.58
2008	120,402	1,699	122,101	1.39
2009	109,859	1,615	111,474	1.45
2010	120,903	1,419	122,322	1.16
2011	109,673	1,526	111,199	1.37
2012	133,399	1,717	135,116	1.27
2013	131,118	2,307	133,425	1.73
2014	131,087	2,115	133,202	1.59
2015	137,729	2,053	139,782	1.47
Total	1,226,030	25,996	1,252,026	2.08

The number of violations has been fairly consistent, typically around 1,500-2,000. The exception to this pattern is the year 2006 which had a much greater number of violations, probably because the derogation was not available to farms until 2007. Of particular concern is the upsurge from 2013, which brought the number of breaches above 2,000. Because we exclude farms with a valid derogation, these figures represent a lower bound of overall noncompliance with the quantitative thresholds, since some farms with a derogation still exceed the 250 Kg NPH limit.

3.2 Explanatory variables

The econometric models include a set of independent variables relating to farm or farmer characteristics that may help to explain variations in the probability violation. We follow the selection of explanatory variables used in Lippert et al. (2014) to guide our expectations on how a characteristic is likely to determine noncompliance. Farm characteristic variables include lagged NPH values, land size categories and the type of farm ownership structure. There is also a set of variables containing farmer characteristics, which includes the age of the farmer, previous violations and derogations, and when the farmer first registered with DAFM. We include dummy variables for county and year. Our choice of variables and categories within each variable is limited to cases where we had sufficient numbers of observations in the sample. Fortunately, the collected output data on nitrates and land holdings is largely complete and informative.

However, the available dataset on penalties imposed on farms under the regulations contains some gaps in coverage and suffers from some apparent inconsistencies. This means we are not able to use some potential explanatory variables we would ideally like to include, such as the size of the previous penalty for those that were penalised.

Farm Characteristics

Lagged NPH
We include a lagged NPH figure from the previous year as an obvious starting point for explaining the probability of a violation in the current year. We do not expect (or often see in the data) very large changes in livestock on the farm across one year, so last year's NPH farm figure is likely to be strongly related this year's figure, assuming business as usual. Farms that are closer to the 170 Kg NPH limit have less leeway to increase fertiliser use or increase livestock holdings than those farms that have had smaller NPH figures in the past.

Land size
Land size is likely to play a big role in a farm violating the regulation as it is the denominator in the final calculation of a farm's NPH figure. Although there is obviously a positive correlation between land holdings and livestock numbers, farms with greater land holdings should, all else equal, be less likely to violate. There is also evidence that compliance costs place small firms at a competitive disadvantage (e.g. Crain & Hopkins, 2001). It is likely that regulation impinges more on smaller farms, assuming that they have more limited time and resources and therefore are less able to spread compliance costs across a wide base. Thus, we hypothesise that smaller farms are likely to violate the regulations more often.

Farm Ownership Structure
Slemrod (2007) discusses the potential asymmetric compliance between individuals and businesses, based on differential incentives. Individuals bear full responsibility of any penalty that may arise if regulations are broken and, hence, may be inclined to be risk-averse. Businesses, by contrast, may operate in a more risk-neutral manner. They may also be affected by principal-agent problems, whereby the agent responsible for compliance decisions faces different incentives from the business owner. These arguments could apply to farm behaviour in Ireland, which has three types of structure: an individual, a company, or a joint venture.[11] The large majority of Irish farms are held by individuals. Of particular interest may be joint ventures, which occur when two separate farms decide to join together in a farm partnership and report to DAFM as one entity. We might expect farms in joint ventures to fall foul of the regulations more often, as any potential penalty will be shared.

Farmer Characteristics

Age
We do not have a clear directional hypothesis in relation to the age of the farmer. On the one hand, older farmers are likely to have more experience in farming techniques and in dealing with national and EU regulations. This experience might reasonably be expected to lower the probability of violations. On the other hand, older farmers may be less likely to change long-standing farm practices. Buckley et al. (2015) examine the adoption of nutrient management practices across farmers and find variables like age and off-farm employment negatively affect take up of these best practice schemes. Such resistance to change may mean that older farmers are less likely to manage nutrients and hence more likely to violate the regulations. We do not possess data on second jobs a farmer may undertake at present.

Time of initial registration with DAFM
The data indicate when a farm first registered with DAFM and was given a herd number. This registration date is used as a proxy for the level of contact a farm has had with DAFM. Farmers that have built up a relationship with the Department may be more aware of regulatory requirements and informal advice that could assist them in complying with Nitrates Regulations. As this requirement was only brought in the late 1990s but most farms had been in operation for a period before that, we assign all farms in operation before 1998 the same year registration date.[12] We create a dummy variable taking the value of 1 if a farm has a registration date before 1998, and 0 otherwise.

[11] That being said, European (and Irish) farms are typically run as family businesses as highlighted by Herzfeld & Jongeneel (2008).

[12] Similar to a driving licence.

Previous violation(s)
We create a set of dummy variables to indicate breaches of the Nitrates Regulations in previous years: a value of 1 in the first variable indicates that the farm violated the regulation last year and a 1 in the second variable indicates that the farm had a violation two or more years ago.

Previous derogation(s)
We also create a dummy variable that records whether a farm had been granted a derogation in the previous year. Farms that move from having a derogation to not having one have to adapt their behaviour to comply with the lower NPH limit. We expect that this adjustment process may trigger breaches of the regulation for some farms.

Data cleaning was undertaken and extreme values for some variables were omitted. In particular, we exclude farms with a land size smaller than 1 hectare. We choose this figure as farmers need to have at least one hectare of eligible land to qualify for the Basic Payment Scheme.[13] Some summary statistics are displayed in Table 2.

Table 2: Summary Statistics

Variable	Mean	Std. Dev.	Min.	Max.	Observations
NPH	72.9	70.4	0	8,393	1,264,629
Age	53.3	13.9	16	105	1,119,697
Land Size(Ha)	36.1	34.6	1	1,527	1,192,979

4. Methods

We employ two types of binary logistic regression (logit) model: (1) random effects panel models estimated over data from multiple years; (2) single-year cross-sectional models estimated from data for a single a year. Panel models exploit the fact that we have repeated observations over time of the same farms, allowing us to control farm-level unobserved characteristics. However, such models require us to make some assumptions about the underlying distribution of the probability that farms are in violation and also about the stability of the relationships between covariates and the probability of violation. Hence we report both types of model.

4.1 Random effects model

Our baseline panel model (1) is shown below:

$$ln\left(\frac{Pr[Violation_{ij} = 1]}{(1 - Pr[Violation_{ij} = 1])}\right) = \beta_0 + \beta_m \sum_{i=1}^{m} \boldsymbol{X}_{ij} + \beta_n \sum_{i=1}^{n} \boldsymbol{Y}_{ij} + \alpha_i + \varepsilon_{ij} \quad (1)$$

Here the probability that an individual farm, i, violates the regulation in a certain year, j, is modelled as a function of a matrix of farm characteristics, $\mathbf{X}_{ij}$, and another matrix of farmer characteristics, $\mathbf{Y}_{ij}$. The term α_i captures variation in the underlying propensity of individual farms not to comply with the regulations, which we assume is normally distributed. The list of farm and farmer characteristics is as detailed previously in Section 3.2. Our regression analyses are run in Stata 14.

[13] https://www.ifa.ie/bps/#.Woq9uK5l99N

Regression results are reported in the form of odds ratios that compare the odds of a violation occurring in one group against those of a reference group. An odds ratio of greater than one indicates a greater likelihood of violation, while an odds ratio of less than one indicates a lower likelihood of violation. For example, if the reference category for the age variable were 51-60 years old and we reported an odds ratio of 2 for the 16-40 year old category, that would imply that the odds of a violation were twice as high among 16-40 year olds than among the reference category. Correspondingly, an odds ratio of 0.5 would imply that the odds of violation were half as high for this group as among those of the reference category.

4.2 Cross-sectional models

We also estimate cross-sectional logit models for each individual year in the dataset. However, the logit model for the year 2015 is used for prediction purposes, as this is the final full year of data we possess. We set the prediction threshold to balance the sensitivity (ability of the model to predict true positives) and specificity (ability to predict true negatives) of the model. This parameter may be adjusted depending upon the objectives of the analyst; for example, one might wish to ensure that all likely violators are included in the predicted group even at the cost of an increased number of false positives. The 2015 model coefficients have also been adapted for use in a ready-reckoner that generates a likelihood of violation for a farm with specific selected characteristics. This kind of model can help to inform trials to test interventions designed to reduce noncompliance, by targeting those farms that are most likely to violate for an intervention.

4. 3 Robustness test

To test whether our models have reasonable predictive performance given the set of variables included in them, we compare their results to those from the LASSO (Least Absolute Shrinkage and Selection Operator) estimator (Tibsharani, 1996) which penalises the use of regressors that contribute little to the fit of the model. We use this model selection tool mainly as a robustness check to see whether restricting the extensive set of explanatory variables could improve its predictive performance. The Stata add-ins developed by Ahrens *et al.* (2018) are used for Lasso modelling. This check involves re-estimating the 2015 cross-sectional model using the cvlasso command and selecting the preferred set of regressors based on 10-fold cross-validation. The optimal set of control variables and the resulting coefficients can then be compared to their OLS equivalents for the full model.

5. Results

5.1 Regression output

Table 3 presents regression results obtained from the estimation of the baseline model set out in Section 4. The two models of (1) Random Effects; and (2) Individual year logit for 2015 are given. The full set of cross sectional logit models for individual years is provided in the Annex.

Table 3: Regression results for panel and cross-sectional regression models; odds ratios

Dependent Variable: Violation	**(1) Random effects b/se**	**(2) 2015 cross-section b/se**
Lagged NPH (ref: 150-155)		
0-50	0.043*** (0.003)	0.069*** (0.010)
50-100	0.055*** (0.004)	0.101*** (0.015)
100-120	0.131*** (0.009)	0.212*** (0.033)
120-140	0.302*** (0.019)	0.437*** (0.062)
140-150	0.640*** (0.040)	0.600*** (0.093)
155-160	1.305*** (0.087)	1.214 (0.193)
160-165	1.964*** (0.122)	1.341* (0.207)
165-170	2.555*** (0.157)	2.166*** (0.329)
170-172	2.924*** (0.258)	2.264*** (0.509)
172-180	2.353*** (0.390)	2.939*** (0.637)
180-250	3.666*** (0.587)	3.288*** (0.658)
250+	6.749*** (1.166)	4.259*** (1.040)
Land Size (ref: 30-40ha)		
1-5ha	6.883*** (0.423)	5.465*** (0.621)
5-10ha	2.904*** (0.153)	2.585*** (0.275)
10-15ha	1.824*** (0.098)	1.697*** (0.186)
15-20ha	1.408*** (0.078)	1.447*** (0.163)
20-25ha	1.297*** (0.073)	1.306** (0.154)
25-30ha	1.132** (0.065)	1.223* (0.148)
40-50ha	0.852*** (0.045)	0.951 (0.110)
50-75ha	0.672*** (0.034)	0.787** (0.087)
75-100ha	0.555*** (0.042)	0.776 (0.122)
100+ha	0.412*** (0.042)	0.479*** (0.107)
Violation last year	1.192 (0.185)	1.470** (0.249)
Violation two or more years ago	1.993*** (0.063)	1.830*** (0.122)
Derogation last year	0.948 (0.058)	0.178*** (0.031)
Age (ref: 51-60)		
16-40	1.307*** (0.056)	0.965 (0.100)
41-50	1.154*** (0.040)	1.094 (0.083)
61-70	0.895*** (0.034)	0.893 (0.067)
71+	0.744*** (0.037)	0.782*** (0.071)
Dummy=1 if farm registered before 1998	1.034 (0.031)	1.164** (0.076)
Farm Structure (ref: Individual)		
Joint Venture	0.977 (0.164)	0.957 (0.373)
Year Dummies	Yes	No
County Dummies	Yes	Yes
No. of obs.	671,030	110,422
No. of Groups	116,444	

Note: Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Across the two models, we see that both the lagged NPH and the size of the land holding have a consistent relationship with the likelihood of violating the regulations. Farms with greater NPH figures in the previous year are much more likely to violate the regulations. It is notable that there is no step-jump in the likelihood of noncompliance associated with previous NPH figures, but rather a steady and substantial increase; higher NPH in the previous year just steadily increases the probability of noncompliance in the current year. With respect to land size, smaller farms are substantially more likely to be in breach of the regulations. These results are robust to using different specifications.

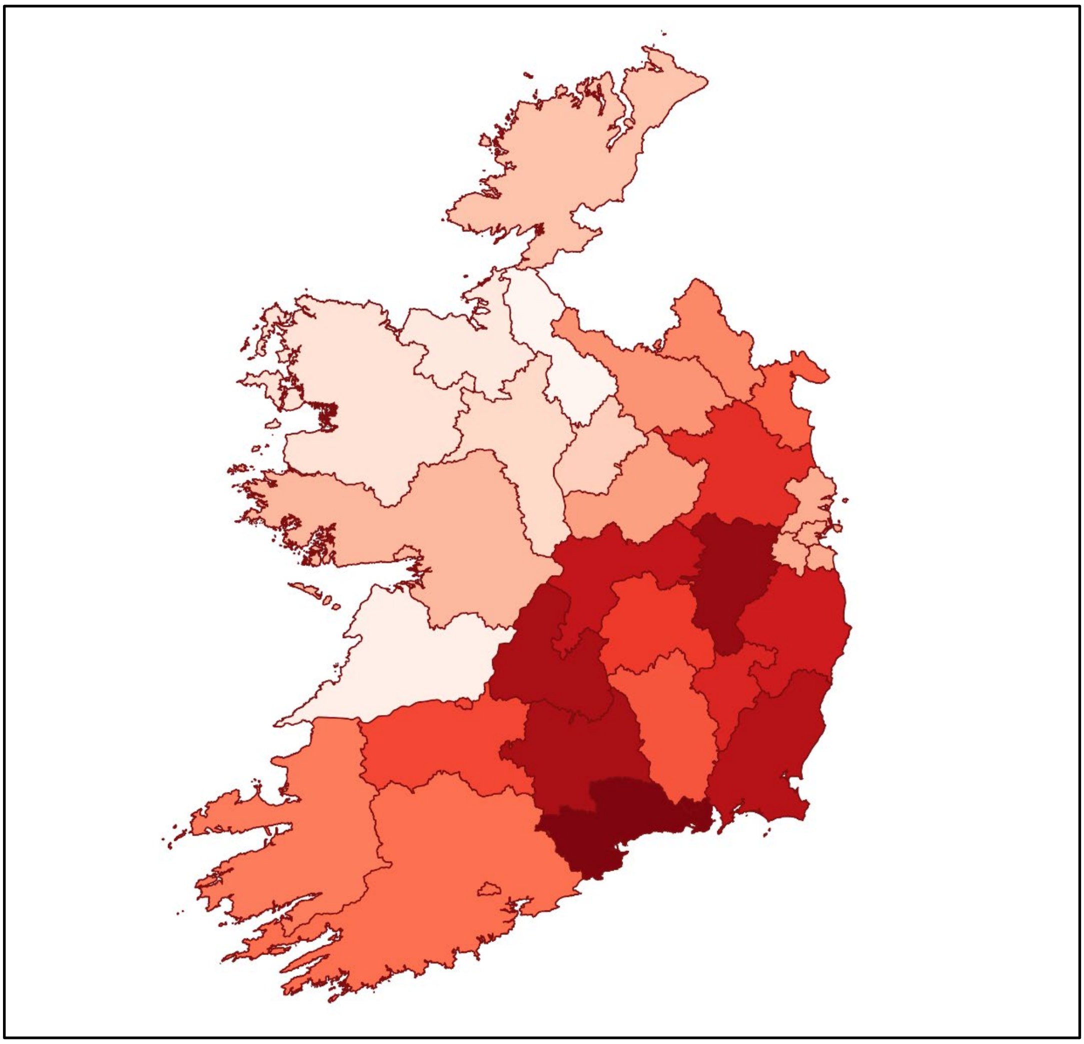
One explanation for the greater propensity of smaller farms to be in noncompliance is straightforward: it takes less change in livestock or fertiliser quantities to generate noncompliance. It is also possible that these farms deliberate more on whether the value of extra livestock or extra fertiliser is greater than the potential penalty cost of a breach. As the penalty for violating the regulations is a percentage reduction in a single farm payment, the value of which increases as land holdings increase, smaller farms face a smaller penalty value when making livestock and fertiliser use decisions.

The age of the farmer is also an important predictor of violations. Younger farmers are more likely to be in noncompliance in the random effects model. This effect is significant in the majority of cross sectional models (see Annex) although this does not hold in all years, including 2015. The oldest category of farmers i.e. those who are over 71 years of age, are less likely to breach compared to those of average farmer age. This finding remains true across both models in Table 3 and the majority of individual year models.

Previous violations are shown to be positive indicators of a violation when allowing for random effects. The random effects model includes farms regardless of violation history, so the odds ratios reflect the estimated odds of violation relative to a farm that has no previous violations. The coefficients confirm that repeat offenders make a substantial contribution to noncompliance. For farms that had a derogation in the previous year, a previous derogation reduces the probability of a violation in both models, although this is only statistically significant in the cross-sectional model.

No statistically significant relationships are found for farm ownership structure or the registration time with the Department.

Figure 1: County-level fixed effects on odds of nitrates violation (Random effects model)



The map (Figure 1) displays the odds ratios for each individual county dummy in the random effects model. The darker the shade of red, the higher the odds that a farmer from that county will be in violation of the regulations, after allowing for the farmer's and farm's characteristics. Cork is used as the reference county category as this is the county with the most farms. Table 8 in the Annex displays the full county level fixed-effects and indicates whether they are statistically significant. We immediately see that farms situated in the East and South East of the country are more likely to be in breach of the Nitrates Regulations. County Waterford has the highest rate. In contrast, farmers in the West are less likely to violate the regulations all other things equal, with farms in County Leitrim having the smallest likelihood.

A possible reason for these differences is the relationship between stocking rates and land quality. Better land quality allows farmers to increase their stocking rate more easily and farms with greater livestock numbers per unit of land are more likely to breach the 170 NPH limit. Counties where farmers are more likely to violate the regulations such as Kildare and Waterford tend to have good land quality.[14] The county effects map bears a striking resemblance to maps illustrating the length of grazing season in Ireland, for example in Collins & Cummins (1996, p.155) and found in the Annex (Figure 3). This figure shows that the south and east of the country can have a longer grazing season

[14] Poaching, which is the damage to grassland from the feet of livestock, is a potential consequence from greater stocking rates, even on land of good quality.

by up to 60 days/year than the north and west of the country. This relationship between the grazing season and stocking rates could potentially be driving the pattern of county effects.[15]

A similar picture emerges when considering the odds ratios for each individual county dummy in the 2015 cross-sectional model (see Figure 2 in the Annex). Again, the propensity to violate the regulations is much higher in counties in the South East of the country, although many of the individual county level fixed-effects in the 2015 model are short of statistical significance.

5.2 Prediction tests

We can compare the predictive power of our models to DAFM's current rule-of-thumb of targeting those farms with an NPH figure of over 150 Kg NPH for additional compliance encouragement. By excluding the year 2015 from the data, we can assess predictive performance for 2015 based on data for 2014 and previous years. We compare both the performance of the panel models (data on all years 2006-2014) as well as the individual year model (2014 only) to the 150 KG NPH rule. We use a threshold probability cut-off of 0.0208 when predicting a case as a violation or not, which corresponds to the probability of violating the regulations across the period 2006-2015. Table 4 compares the classification performance of the four models, reporting sensitivity and specificity. Sensitivity measures the proportion of actual positives that are correctly identified i.e. the probability of detecting a violation. Specificity measures the proportion of actual negatives that are correctly identified i.e. the true negative rate of farms in violation.

DAFM's rule-of-thumb is to target farms with an NPH figure over 150 Kg, which prompts just under 11,000 letters to be sent out to warn about a potential farm breach and encourages ways for farmers to reach compliance. This rule achieves a detection rate of 56%. While our models outperform this in terms of correctly identifying those who do violate the regulations, they are less successful at correctly classifying those that do not violate the regulations. For the efficiency of the regulatory system, this is a trade-off between the ability to identify more of these likely violators and being able to mitigate the consequences of nitrates violations versus greater administrative costs in terms of correspondence to farms. We argue that false positives (i.e. farms that are flagged as violators but do not violate) are less important to DAFM than false negatives (i.e. farms that do not receive targeted correspondence but do violate). Our aim then is to improve on the Department's sensitivity figure of 56% of violators correctly identified, without an excessive increase in the number of false positives and the subsequent administrative burden.

Table 4: Comparison of models' performance in predicting 2015 outcomes (%)

	Department 150 Rule	***R.E. Model***	***Cross-sectional Model (2014)***
Sensitivity	56	64	70
Specificity	93	91	89
Correctly Classified	92	91	88
Number of Letters	10,786	10,758	13,928

Note: Figures rounded to 1 percentage point.

[15] Differing organic content in soils could also be a potential explanation of the map. https://www.agriculture.gov.ie/media/migration/ruralenvironment/environment/nitrates/2018/SoilsWithOrganicMatteContentForestBareRkExcluded050118.png

We alter the threshold probability cut-off to investigate the impact on the performance of the random effects model in terms of specificity and sensitivity. Tables 5 and 6 display the prediction performance of both models as the threshold changes.

Table 5: Impact of the threshold level on prediction performance for the random effects panel model and the balance between sensitivity and specificity (%)

Threshold	***0.05***	***0.03***	***0.01***	***0.0075***	***0.001***
Violators detected	50	59	73	77	97
True negative rate	95	93	87	83	34
Correctly Classified	95	93	87	84	35
Number of Letters	6,217	8,830	15,947	19,646	76,087

Note: Figures rounded to 1 percentage point.

Table 6: Impact of the threshold level on prediction performance for the cross-sectional model and the balance between sensitivity and specificity (%)

Threshold	***0.05***	***0.03***	***0.01***	***0.0075***	***0.001***
Violators detected	58	65	77	82	100
True negative rate	93	91	83	78	10
Correctly Classified	93	90	83	78	12
Number of Letters	8,793	11,524	20,397	26,038	103,639

Note: Figures rounded to 1 percentage point.

These results illustrate the trade-off between sensitivity and specificity in prediction classification when setting a threshold probability cut-off. We observe that as the threshold probability is reduced, cases are more likely to be classified as violations. This improves the sensitivity of the model with the trade-off of reducing the specificity. Because the number of violations is small in relation to the sample, this has the impact of reducing the overall classification performance of the model. For example, a model that classifies all farms as not in violation will have a correctly classified percentage figure of over 90%, yet this is a poor model for identifying potential farm violators.

With a very low threshold probability of violation cut-off of 0.001, we can identify almost all of the violators with a 100% true positive rate. This may be of great benefit to DAFM, knowing all likely violators will have been contacted and potentially trigger a behavioural response to comply. However, this comes at the great administrative cost of wrongly targeting around 85% of compliant farmers and so does not excel as a predictive model. Ultimately, the use of the predictive models depends on the costs of the interventions they are used to support. They can be used to set a minimum proportion of violators detected or a maximum number of letters to send out to farms, depending on objectives and costs. To bring about this flexibility in terms of the statistical models, we have created a ready-reckoner that generates a probability of violation for a farm when a set of farm characteristics have been specified. DAFM can adjust the threshold probability level at which a farm is predicted to be in violation to suit their needs. This tool can prove to be very effective, particularly when assessing on a farm by farm basis.

5.3 Robustness test

As discussed earlier, we use the LASSO estimator to check if a selecting a more parsimonious set of control variables might help improve the predictive performance of the 2015 cross-sectional model. We then compared the set of regressors and the resulting coefficients to their OLS equivalents. The LASSO results suggest that the vast majority of coefficients do contribute to the predictive performance of the model. Three county effects (Galway, Kilkenny and Sligo) are omitted in the preferred specification, implying that they are not greatly different from Cork. However, omitting these variables has little effect on the other coefficients or on the fit of the model.

6. Discussion and future research

In the context of ongoing regulatory difficulties in reducing the level of noncompliance with the Nitrates Regulations, this study employed administrative data on Irish farms to investigate and identify associations between noncompliance and the characteristics of individual farms and farmers. A combination of statistical models was used to determine which farms are most likely to be in noncompliance. The models yielded clear results. Farms with smaller land holdings and those with previous violations are significantly and substantially more likely to violate the regulations. In addition, there is a systematic relationship between compliance and the age of the farmer, with older farmers are more likely to comply with the regulatory limit, as well as a pattern of varying compliance by county. The models can also be employed to estimate predicted probabilities of noncompliance, with a view to identifying a subset of farms for targeting interventions. In this regard, the findings show that the models outperform a simple rule-of-thumb based on a threshold level of NPH.

These results have the potential to be used to assist farmers in avoiding a loss of income through penalties for exceeding regulatory limits. The use of equivalent statistical models based on the most up-to-date data offers the possibility of targeting farmers most at risk of noncompliance with informational or behavioural interventions. A further benefit of the comprehensive administrative data is that such interventions can be tested for effectiveness through randomised controlled trials, which can be conducted on the complete population of farms and with comprehensive data. A combination of modelling and trials makes it possible to underpin regulatory efforts with more analytical rigour in order to reduce violations of the Nitrates Regulations, with the ultimate goal of decreased nutrient pollution in watercourses. Generally, better land management of farms, including more viable long-term stocking rates, can generate positive externalities for local ecosystems.

While the statistical models are useful for understanding associations and targeting interventions, they offer limited insights into the root causes of noncompliance. The current exercise had no access to information on comprehension of the regulations, inattention to the regulations, attitudes towards the regulations and/or regulators, the administrative burden of the regulation, or the technical abilities of farmers, any of which could in principle affect compliance. Recall, however, that the majority of farms that exceeded the 170 Kg NPH limit were not in breach the previous year. The implication is, naturally, that something on the farm must have changed. In this context, it is notable that the present findings show that the probability of noncompliance increases substantially and steadily with the previous year's NPH figure. This implies that many violations do not occur because of minor changes in on-farm practice, but appear to reflect failure to observe the regulatory limit when increasing stocking rates or when changing the size of the land holding, in some cases appreciably.

Buckley et al. (2015) found older farmers to be more resistant to the adoption of improved nutrient management practices. Yet our models show that older farmers are more likely to comply with the regulations. At first sight, given that the regulations are in part designed to improve nutrient management, this might seem contradictory. However, the simple explanation may be that older farmers are less likely to seek to change the business. It is when change occurs, for instance when expanding the business, altering production, or perhaps selling land, that noncompliance becomes more likely. Note that the smaller the farm, the higher the chance that any given change takes the farm beyond the regulatory NPH limit.

One important limitation of the current study is that it could not address directly the incentive effects of punishment. An important issue may be the lag between noncompliance and punishment. The loss of income is not felt until the year after the breach and then only as a foregone gain (i.e., a reduction in a payment). Herzfeld & Jongeneel (2008) detail potential reasons for agricultural noncompliance drawing on psychological and sociological literature, including Prospect Theory (Kahneman and Tversky, 1979), which implies that farmers would be more likely to alter their behaviour if penalties were experienced as losses rather than foregone gains.

This paper also offers one demonstration of how government departments can make greater use of the combination of administrative data and modern statistical techniques. The notion of "big data" refers to possibilities for collation and analysis conferred by digitisation and the power of modern computers. It is only in recent years that datasets the size of the one analysed in this paper can be manipulated and subjected to proper statistical modelling. In this way, relatively small effects located in datasets that cover large populations have the potential to translate into significant efficiency savings. Here, we have made a start in applying such techniques to nitrate pollution on Irish farms. There is the possibility of adding further to the data thus far compiled, to include socio-economic characteristics of farmers (such as educational attainment), whether farmers have a second job, whether they have access to a farm adviser, the spatial characteristics of farms, and so on. All of these factors may have an impact on the likelihood of compliance with the Nitrates Regulations. The building of such large datasets for policy and regulatory analysis has much potential, within the domain of agriculture and elsewhere.

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Annex

Table 7: Regression results from cross-sectional models with data from individual years; odds ratios

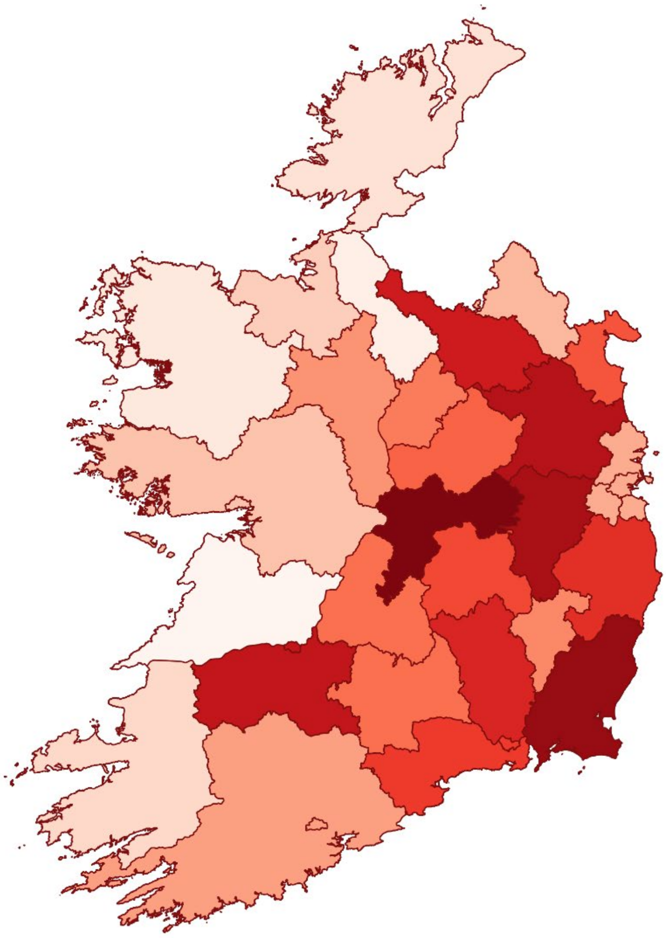
Dependent Variable: Violation	**(1) 2009**	**(2) 2010**	**(3) 2011**	**(4) 2012**	**(5) 2013**	**(6) 2014**
Lagged NPH (ref: 150-155)						
0-50	0.05***	0.09***	0.02***	0.04***	0.03***	0.04***
50-100	0.05***	0.09***	0.07***	0.06***	0.04***	0.05***
100-120	0.11***	0.17***	0.17***	0.16***	0.09***	0.13***
120-140	0.35***	0.35***	0.40***	0.34***	0.26***	0.21***
140-150	0.64**	0.77	0.80	0.65***	0.60***	0.67***
155-160	1.22	1.38	1.72**	1.49**	1.13	1.21
160-165	2.41***	1.77***	2.89***	1.81***	1.69***	2.08***
165-170	3.01***	2.09***	3.93***	2.29***	2.17***	2.70***
170-172	2.47***	3.76***	5.76***	2.36***	2.85***	2.73***
172-180	3.38*	2.73e+06***	6.39**	0.65	1.32	3.94
180-250	5.72***	5.31e+06***	13.17***	0.90	2.00**	6.78*
250+	10.83***	1.03e+07***	24.31***	1.84	3.07***	11.34**
Land Size (ref: 30-40ha)						
1-5ha	6.22***	4.32***	3.87***	4.06***	6.26***	4.35***
5-10ha	3.17***	2.54***	2.03***	2.18***	3.19***	1.95***
10-15ha	1.83***	1.39**	1.43**	1.79***	2.42***	1.28**
15-20ha	1.30*	1.32*	1.34**	1.24*	1.68***	1.09
20-25ha	1.13	1.11	1.13	0.98	1.68***	1.20
25-30ha	0.96	1.22	1.25	0.96	1.15	0.96
40-50ha	0.93	1.00	0.92	0.72***	0.85	0.73***
50-75ha	0.64***	0.69***	0.68***	0.53***	0.77**	0.73***
75-100ha	0.69*	0.79	0.58***	0.31***	0.66***	0.46***
100+ha	0.47***	0.49**	0.41***	0.36***	0.41***	0.47***
VIP_lagviolation1	1.76	0.00***	1.13	6.50*	2.34***	0.74
VIP_lagviolation2	1.78***	2.23***	2.04***	1.90***	2.07***	2.06***
lagderog1	1.34*	0.99	2.84***	0.13***	1.10	0.78*
Age (ref: 51-60)						
16-40	1.30**	1.00	1.35**	1.29**	1.37***	1.48***
41-50	1.08	1.01	1.22**	1.37***	1.14*	1.10
61-70	0.94	0.80**	1.02	1.10	0.88	0.83**
71+	0.83	0.70**	0.97	0.91	0.75**	0.63***
Dummy=1 if farm has 1980 registration date	1.04	0.98	1.08	0.90	0.92	1.07
Farm Structure (ref: Individual)						
Joint Venture	0.75	0.79	0.96	0.70	0.90	1.54
County Dummies	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	88,613	89,530	88,798	92,126	98,718	102,823

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: County-level fixed effects on odds of nitrates violation (Cork is used as the reference county)

Dependent Variable: Violation	**(1) Random effects b/se**	**(3) 2015 cross-section b/se**
Carlow	1.159	1.014
	(0.132)	(0.240)
Cavan	0.917	1.251*
	(0.063)	(0.164)
Clare	0.471***	0.597**
	(0.048)	(0.120)
Donegal	0.787***	0.804
	(0.059)	(0.138)
Dublin	0.819	0.938
	(0.197)	(0.439)
Galway	0.793***	0.877
	(0.049)	(0.116)
Kerry	0.969	0.823
	(0.060)	(0.117)
Kildare	1.438***	1.368
	(0.134)	(0.297)
Kilkenny	1.026	1.249
	(0.076)	(0.187)
Laois	1.140*	1.220
	(0.087)	(0.194)
Leitrim	0.437***	0.604
	(0.074)	(0.204)
Limerick	1.033	1.276*
	(0.064)	(0.164)
Longford	0.755***	1.154
	(0.081)	(0.252)
Louth	1.016	1.196
	(0.111)	(0.276)
Mayo	0.542***	0.606***
	(0.044)	(0.102)
Meath	1.155**	1.314*
	(0.080)	(0.185)
Monaghan	0.919	0.895
	(0.057)	(0.121)
Offaly	1.299***	1.695***
	(0.095)	(0.247)
Roscommon	0.680***	1.002
	(0.064)	(0.179)
Sligo	0.529***	0.853
	(0.068)	(0.189)
Tipperary	1.389***	1.179
	(0.073)	(0.137)
Waterford	1.531***	1.233
	(0.114)	(0.200)
Westmeath	0.879	1.187
	(0.079)	(0.227)
Wexford	1.324***	1.503***
	(0.093)	(0.217)
Wicklow	1.232*	1.239
	(0.132)	(0.278)

Figure 2: Violation county map of Ireland (2015 data only)



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