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Empirical evaluation of nonpoint pollution policies under agent heterogeneity: regulating intensive dairy production in the Waikato region of New Zealand*

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Models used for policy evaluation rarely consider firm heterogeneity, despite its importance for instrument design. This study considers agent heterogeneity explicitly in the evaluation of policies for nonpoint pollution control through the integration of decomposition and calibration procedures for programming models. The application concerns the regulation of nitrate leaching from intensive dairy production in the Waikato region of New Zealand. Failing to represent firm heterogeneity leads to widely different estimates of mitigation costs, relative to where heterogeneity is considered. Variation in baseline emissions and the slopes of abatement cost curves between firms renders a differentiated policy less costly than a uniform standard. However, the relative values of these policies are not broadly different, as firms required to do the most abatement – intensive farms with large baseline pollutant loads – can do so more cheaply, on average.

Key words: differentiated instruments, environmental policy, heterogeneous agents.

1. Introduction

Intensive dairy production continues to place pressure on the quality of freshwater resources throughout Australia and New Zealand, particularly through the elevation of nitrogen (N) and phosphorus levels. For example, nitrate levels are rapidly increasing in the Waikato River, the primary waterway in New Zealand's main dairy-farming region (Vant 2008). Over half of this river's tributaries possess unsatisfactory levels of nitrate owing to emissions from pastoral agriculture (Semadini-Davies *et al.* 2009). Furthermore, the Gippsland Lakes catchment of Victoria will require substantial adoption of less-intensive land management practices, including high uptake of currently

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recommended mitigation practices (CRMPs) in dairy enterprises, to achieve recommended reductions in nutrient load (Roberts *et al.* 2010). N leaching from dairy farms is strongly related to stocking rate and fertiliser application (Monaghan *et al.* 2007). There is scope, therefore, to reduce emissions without abandoning dairy production, particularly with the adoption of CRMPs.

Regulatory bodies are becoming increasingly aware of the need to restrict the substantial environmental impacts of dairy production (Monaghan *et al.* 2007). Minimising the cost of achieving an aggregate emissions target requires that marginal abatement costs are equalised across dairy farms. For this reason, the cost-effectiveness of a policy differentiated between polluters, relative to a uniform abatement standard, is proportional to abatement cost heterogeneity within a regulated population (Newell and Stavins 2003). However, in the situation where differences in abatement costs are minor, uniform policies may be favourable owing to their lower administrative cost. Which policy is superior is case-specific, and this can be informed through detailed empirical research.

Nevertheless, the consideration of firm heterogeneity in empirical models that allow the comparison of uniform and differentiated policies is extremely rare. Studies of environmental improvement in agricultural catchments typically disregard the presence of multiple agents through either aggregation or the analysis of representative firms. Highly informative models can be constructed using the aforementioned approaches; recent Australian examples include studies in the area of water allocation (Adamson *et al.* 2007) and salinity management (Kingwell and John 2007). However, the importance of firm heterogeneity in the relative value of uniform and differentiated instruments suggests that this factor is important to consider in policy evaluation. Factors inhibiting the representation of agent heterogeneity include increased computational complexity and problems with model calibration. Nonetheless, integration of established procedures for the calibration and decomposition of mathematical programmes allows these technical constraints to be efficiently overcome (Doole 2010).

The objective of this research is to compare the relative efficiency of uniform and differentiated emissions standards for regulating nitrate emissions on 498 disparate dairy farms in the Waikato region of New Zealand. It utilises the computational approach of Doole (2010) but extends it to consider around five times as many farms, simulation of a much wider range of recommended mitigation practices on each dairy farm, and policy targets defined by emissions, rather than inputs. The optimisation model contains over 3 million constraints and provides a detailed description of important processes that should ideally be considered in the design of appropriate regulatory instruments for heterogeneous dairy farms. Statistical analysis of model output is used to examine why the costs imposed by differentiated and uniform policies are not broadly disparate.

The next section describes the conceptual framework. Section 3 describes the empirical model, while Section 4 presents the results and discussion. Section 5 concludes.

2. Conceptual framework

It is common practice in agri-environmental policy analysis to assume that agricultural management within a catchment can be adequately described by a single, representative farm model. This pragmatic computational approach reduces model size and data requirements and can be defined as follows:

$$\max_{\mathbf{x}} z = \pi(\mathbf{x}),$$
$$\text{subject to } g_r(\mathbf{x}) - b_r \leq 0 \ \forall r, \quad r = [1, \ldots, m], \ h(\mathbf{x}) - d \leq 0 \text{ and } \mathbf{x} \geq \mathbf{0}, \tag{P1}$$

where z is total profit, $\pi(\mathbf{x})$ is a profit function, r is the constraint index, m is the total number of resource constraints, $g_r(\mathbf{x})$ denotes a constraint function, b_r is a fixed resource endowment, $h(\mathbf{x})$ describes the relationship between farm management and the emission of a nutrient damaging to water quality, d is an emissions target, and $\mathbf{x}$ is a vector of management variables with $\mathbf{x} \in X$, where X is a given subset of $\Re^n$.

The representative farm approach introduced in P1 disregards important inter-farm differences in capital, efficiency, and management. Thus, where sufficient data are available, additional insight may be gained through the explicit analysis of individual farms. Suppose that a catchment consists of j agricultural producers. The nonlinear optimisation problem faced by each farmer j in the absence of regulation may be stated as follows:

$$\max_{\mathbf{x}^j} z^j = \pi^j(\mathbf{x}^j),$$
$$\text{subject to } g_r^j(\mathbf{x}^j) - b_r^j \leq 0 \ \forall r, \quad r = [1, \ldots, m^j] \text{ and } \mathbf{x}^j \geq \mathbf{0}, \tag{P2}$$

where superscripts denote membership to farmer j.

Assume that the autonomy of each producer is maintained through perfect competition in factor and output markets, but a regulatory policy is introduced that affects each producer uniformly. This uniform policy represents an equal proportional reduction in the baseline level of leaching for each farm in the catchment. The catchment problem may be stated as follows:

$$\max_{\mathbf{x}^j} z = \sum_j \pi^j(\mathbf{x}^j),$$
$$\text{subject to } g_r^j(\mathbf{x}^j) - b_r^j \leq 0 \quad \forall r, j, \quad h^j(\mathbf{x}^j) - d^j \leq 0 \quad \forall j \text{ and } \mathbf{x}^j \geq \mathbf{0} \quad \forall j. \tag{P3}$$

Here, $h^j(\mathbf{x})$ describes the relationship between management and emissions on farm j and d^j is a firm-specific emissions target. The dimensionality of P3 highlights the high data requirements and extensive calibration required in a multi-agent model. Nevertheless, the solution to P3 can be identified efficiently through collection of the optimal solutions to each individual firm problem:

$$\max_{\mathbf{x}^j} z^j = \pi^j(\mathbf{x}^j),$$
$$\text{subject to } g_r^j(\mathbf{x}^j) - b_r^j \leq 0 \; \forall r, \; h^j(\mathbf{x}^j) - d^j \leq 0 \text{ and } \mathbf{x}^j \geq \mathbf{0}. \tag{P4}$$

Instead, assume that a differentiated policy is introduced. This allows the level of decrease to vary by farm. It complicates optimisation because the sub-problems P2 are linked through an emissions constraint. In this case, the catchment problem P3 may be stated alternatively as follows:

$$\max_{\mathbf{x}^j} z = \sum_j \pi^j(\mathbf{x}^j),$$
$$\text{subject to } g_r^j(\mathbf{x}^j) - b_r^j \leq 0 \; \forall r,j, \; r = [1,\ldots,m^j]; \tag{P5}$$
$$\sum_j h^j(\mathbf{x}^j) - d \leq 0 \quad \text{and} \quad \mathbf{x}^j \geq \mathbf{0} \quad \forall j,$$

where $\sum_j h^j(\mathbf{x}^j) - d \leq 0$ is an individual coupling constraint. P5 differs from P3 because the environmental goal specified in d is not defined for each producer. Rather, optimal pollutant loads for firms are determined individually as part of the optimal solution. This allows the identification of the differentiated policy that minimises abatement cost across the catchment through equalising marginal abatement cost across farms. However, it complicates model solution because P5 is no longer separable, in contrast to P3, even though its block-angular structure is sparse.

3. Empirical model

3.1. Background

The New Zealand dairy industry is this nation's largest export earner and accounts for approximately a third of international dairy trade. High milk prices over the last decade have promoted input intensification, with mean livestock intensity increasing by 12.5 per cent (Livestock Improvement Corporation, 2009) and nitrogenous fertiliser use increasing by more than 300 per cent over 1997–2007 (Environment Waikato, 2008). Intensive dairy production substantially promotes nitrate leaching. The amount of N excreted by grazing animals is the primary source, as ryegrass-dominant pastures generally provide more N than is required (Monaghan *et al*. 2007).

The Waikato River in New Zealand's North Island is becoming increasingly polluted from nitrates emitted from dairy production (Vant 2008). Subsequent algal blooms have decreased the value of this waterway for recreation and tourism. Thus, there is an important need to establish appropriate regulatory tools to decrease diffuse emissions from dairy farming. This application contributes to this objective through the development of a multi-agent catchment model and its use for policy evaluation. This involves an explicit comparison of the P1, P3, and P5 models discussed in Section 2.

The aim of this multi-agent model is to forecast the consequences of environmental policy in the near term (around 5 years). The capacity of farm operations to change by a broad degree is restricted by the constraint sets and calibration function that define the technology and management of each farm. This restrains the capacity of the model to explore issues important in the long run, such as industry contraction and expansion. The model also focuses solely on dairy production, though other land uses – such as sheep and beef production, horticulture, and urban centres – are also present. Thus, it does not allow for the adoption of mitigation practices in these land uses or changes in land use to reduce emissions.

The model is important for a number of reasons, despite these assumptions. First, dairy farming dominates this catchment and is the primary source of nitrate emissions. Second, how mitigation practices and policies impact heterogeneous dairy farms is important given the national significance of dairy farming and a lack of knowledge regarding such factors. Last, the study diverges from the standard approach taken by economists through focussing on a high number of individual firms. This complicates the inclusion of additional land uses, but this extension is the subject of ongoing research.

The total area of dairy production in the Waikato River catchment considered in this study is 61 650 hectares. There are 183 773 cows and 498 dairy farms in this area, with the latter represented individually in P3 and P5. The basic structure of the farm models is presented next. This is followed by a description of their integration in the catchment model.

3.2. Farm model

A brief overview of the farm model is presented here; key model equations are presented in Data S1 (Doole and Pannell 2011). Each farm model provides a detailed description of the integrated processes that exist within the dairy production system. Milk production, stocking rate, farm area, nitrogen fertiliser, and mitigation practices are mostly interdependent within this system. Bioeconomic modelling is a valuable way of considering these relationships in policy evaluation.

The farm model is a static framework involving 26 feed periods over a single year. It is assumed that each farmer wishes to maximise operating profit, revenue minus fixed and variable costs. Firm revenue consists of returns for milk and sales of cull cows and excess calves. Total cost is the cost of supplementary feed purchases, grass silage production, nitrogen fertiliser, variable costs defined per cow, and fixed costs defined per ha.

Individual cows can possess one of 216 different attribute sets. These sets involve different temporal energy demands given differences in calving date, cull status, lactation length, and productivity. Cows utilise energy provided by consumption of grazed pasture, grass silage, concentrates, and maize silage. Pasture area is allocated between grazing, grass silage production, and being rested for future use in any given period. Utilisation of pasture for grazing or grass silage production takes place between minimum and maximum pasture densities that ensure cow intake requirements are met and feed quality is maintained. Maize silage or concentrates can be purchased to complement grass silage feeding in periods of low pasture production, especially in late winter. Moreover, the application of nitrogen fertiliser can promote pasture growth above expected levels and thus provides an alternative strategy to boost available feed.

Nitrate leaching from a given farm is computed as a function of milk production, nitrogen fertiliser application, stocking rate, and maize silage consumption. Leaching loads for each farm also vary by soil type. A number of CRMPs are also represented, unlike Doole (2010). Low-N feed reduces N excretion by livestock. Low-rate effluent application means N is applied more in line with plant requirements. Dairy shed manipulation using a Dungbuster® (Technipharm, Rotorua, New Zealand) system involves the employment of automated yard cleaning to reduce effluent volume. Leaching can be reduced by deferring effluent application until drier periods. A feed pad reduces leaching by removing cows from pasture during wet periods. Nitrification inhibitors reduce leaching by impairing the conversion of ammonium to nitrate during the microbial process of nitrification. The retention of ammonium promotes pasture growth. Nitrification inhibitors and nitrogen fertiliser do not interact directly in the model because leaching is driven mostly by urine patches and hence stocking rate in New Zealand dairy production systems (Monaghan *et al*. 2007).

3.3. Catchment model

The farm model from Section 3.2 is used as a basis for the construction of the P1, P3, and P5 models. Model P1 is constructed based on means of key variables from the full sample of farms in the catchment: farm size, milk production, soil mix, and stocking rate. All farm models in P1, P3, and P5 incorporate fixed farm size and soil types. They are also each calibrated to correspond with their actual stocking rate and milk production for the 2008/2009 milking season (see below). Environmental constraints in P1, P3, and P5 concern the specification of upper bounds for nitrate loads. Individual farm models are coupled in P5 through $\bar{N} \geq \sum_j N^j$, where $\bar{N}$ is an aggregate emissions target and N^j is total emissions from firm j.

Data regarding farm size, soil type, milk production, and stocking rate for each farm are drawn from AsureQuality, DairyNZ, Environment Waikato, Livestock Improvement Corporation, and New Zealand Land Resources Inventory information. These data are used to define the characteristics of individual farms within the representative catchment. However, a lack of more specific information and the high cost of obtaining further data prevent calibration through the inclusion of constraint sets that are fully diversified between agents. Thus, positive mathematical programming (PMP) (Howitt

1995; Henseler *et al.* 2009) is employed as a pragmatic means to calibrate the large number of farm models.

PMP directs a mathematical programming model to return a baseline situation as its optimal solution through the inclusion of a nonlinear calibration function. The calibration function estimated using PMP calibrates the optimisation model to observed production in the base milking season (2008/2009). It thus captures differences in production on farms occurring because of variation in technology and capital allocations and the management skill of producers (Howitt 1995). Use of a concave output function for calibration allows the simultaneous calibration of milk production and cow number in this application. A quadratic total output function is specified for total milk production (Y^j). It is defined $Y^j(x_c^j) = (\varpi^j + \varsigma^j x_c^j)x_c^j$, where ϖ^j is an intercept term, ς^j is a slope coefficient, and x_c^j is total cow number for farm j. The term in brackets on the right-hand side is marginal output or milk production per cow, which decreases linearly with cow number. The use of this specific functional form is motivated by the identification of this relationship in numerous experimental studies (eg Macdonald *et al.* 2008).

PMP has recently been extended in several conceptual studies that propose the use of maximum entropy (ME) methods to calibrate input data so that model output reports observed outcomes (eg Heckelei and Wolff 2003). Use of ME for calibration requires bilevel programming, which is nontrivial for models of realistic complexity. Indeed, this requires *a priori* definition of which constraints are binding, which is impossible in a model of the size studied here and also reduces the integrity of model output. ME is also unsuitable for model calibration given the low amount of data available for this application, because the selection of parameter supports unduly influences the resultant distribution. Accordingly, this study follows typical practice (eg Schmid *et al.* 2007; Henseler *et al.* 2009) and applies PMP without integration with ME.

Solution of the catchment model requires the optimisation of 498 nonlinear programming (NLP) models, independently in P3 and collectively in P5. Each farm model incorporates 6540 constraints and 4600 decision variables. P3 can be solved efficiently as each farm model is independent of the others. In contrast, P5 contains around 3.3 million constraints and 2.3 million decision variables when not decomposed; this is well above the memory restrictions of standard NLP codes.

This limitation can be removed through the use of decomposition techniques for nonlinear optimisation (Conejo *et al.* 2006; Doole 2010). An augmented Lagrangian procedure is employed, which involves appending the coupling constraint to the profit function of each farm model through the use of a shadow price and a quadratic penalty function. This achieves separability in j and allows the sequential optimisation of all farm models in each iteration. The shadow price for the coupling constraint is updated in each iteration until the coupling constraint is satisfied optimally (Doole 2010). Solution efficiency is improved by forming an initial estimate of the shadow price for the coupling constraint based on a smaller catchment sample and using optimal solutions for each farm model from the previous iteration as the starting point for the current optimisation.

3.4. Parameter values

Parameters from the 2008/2009 milking season are used. All monetary values in this paper are stated in New Zealand dollars.

Feed energy, substitution, and utilisation rates are taken from Dexcel (2008a). Average pasture production is taken from Dexcel (2008b). The timing and magnitude of increases in pasture production associated with the use of nitrification inhibitors are provided by Jim Moir (pers. comm., 2010).

Energy demand for each cow attribute combination as a function of grazing, milk production, and pregnancy is computed using a simulation model constructed using information from Dexcel (2008a).

Leachate burdens are calculated for different soil types using numerous combinations of maize silage amounts, milk production, N fertiliser use, and stocking rate using the OVERSEER model (Monaghan *et al.* 2007). The metamodel describing nitrate leaching is generated through linear regression of these data using SHAZAM econometric software (Whistler *et al.* 2004). The efficacy of mitigations is taken as the midpoint from ranges computed in the BMP toolbox (Monaghan 2009).

The milk price for 2008/2009 [$5140/t milk solids (MS)] is taken from Livestock Improvement Corporation (2009). Production costs are drawn from AgFirst Waikato (2009), Chaston (2008), DairyNZ (2009), and Longhurst and Smeaton (2008). The costs of mitigations are taken from AgFirst Waikato (2009), Longhurst and Smeaton (2008), and Monaghan (2009).

All models are solved using the CONOPT3 solver in GAMS Distribution 23.0 (Brooke *et al.* 2008).

3.5. Simulated scenarios

A number of scenarios are evaluated. Section 4.1 describes the heterogeneity of output from the optimisation model. Section 4.2 examines the relative value of uniform (P3 in Section 2) and differentiated (P5 in Section 2) policies using optimisation models of a representative farm and a catchment incorporating heterogeneous agents. Section 4.3 presents output from the optimisation model incorporating heterogeneous agents that describes the mitigation practices used by an individual farm and all farms in the catchment. Section 4.4 employs regression analysis and the theoretical framework of Newell and Stavins (2003) to explain the difference in abatement costs between uniform and differentiated policies. However, the local approximation approach suggested by these authors is not required because the use of a large model incorporating heterogeneous firms obviates the need for reliance on scarce, aggregate data.

The Newell and Stavins (2003) framework is based on the examination of firm heterogeneity through the derivation of firm-specific abatement cost curves. The standard form of the abatement curves estimated from model output is as follows:

$$C^j(q^j) = c^j\left(\bar{q}^j - q^j\right)^2, \tag{1}$$

where C^j is total abatement cost, c^j is a slope parameter (half the slope of the marginal abatement cost curve) (\$ kg/N), $\bar{q}^j$ is total unregulated pollutant emissions (kg N), and q^j is total emissions under regulation (kg N). A higher value of c^j indicates a steeper abatement cost curve and a higher marginal abatement cost, *ceteris paribus*.

The curve defined in Equation (1) does not provide a consistent structure in which to simultaneously consider the baseline leaching level and the slope of the abatement cost curve of each firm and hence the drivers of the relative cost of differentiated and uniform policies. Newell and Stavins (2003) define a curve that allows these factors to be considered through the addition of a scale adjustment (y^j):

$$C^j(q^j) = c^j \cdot [y^j]^2 \cdot \left(a^j - \frac{q^j}{y^j}\right)^2, \tag{2}$$

where y^j is farm size (ha) and a^j is baseline emissions per ha (kg N/ha) with $a^j = \bar{q}^j/y^j$. Equation (1) is obtained by cancelling the y^j term in Equation (2).

Parameter a^j is determined from base model output. Model P3 is used to identify firm-specific, profit-emissions pairs for nitrate restrictions of 0–70 per cent. The c^j parameter is then estimated for each firm using nonlinear regression in MATLAB 7 (Miranda and Fackler 2002). The quadratic functional form as specified by Newell and Stavins (2003) is highly appropriate, with the R^2 across all regressions having a mean of 0.97 and a standard deviation of 0.03.

4. Results and discussion

4.1. Farm heterogeneity

Figure 1 presents probability distributions for key farm parameters that were used to calibrate the individual farms of the catchment model. Most farms are under 150 ha, but there are a number of larger units (Figure 1a), giving a mean area of 124 ha. Stocking rate appears close to being normally distributed (Figure 1b), with a mean of 2.98 cows/ha and a standard deviation of 0.57 cows/ha (Figure 1b). In contrast, the distribution of yield of milk solids per cow is approximately uniform between 250 and 400 kg MS per cow (Figure 1c). The distributions in Figure 1 indicate that there are substantial inherent differences between the 498 individual farms in the catchment.

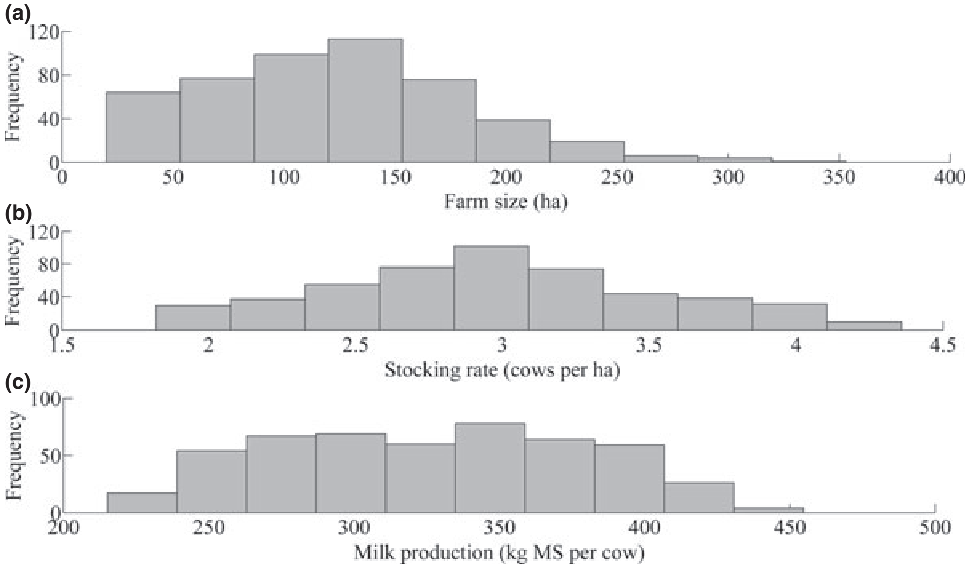

Figure 1 Probability distributions for (a) farm area, (b) stocking rate, and (c) milk production per cow used to calibrate individual farm models.

Following calibration of individual farms to these data, the distribution of profits calculated by the model has a mean of \$1360/ha and a standard deviation of \$786 (Figure 2a). In addition, there is substantial variation in modelled N emissions (Figure 2b), with a mean of 31 kg N/ha and a standard deviation of 8.5 kg N/ha. Overall, these distributions show that there is substantial heterogeneity among firms; failing to represent these differences could potentially mislead policy evaluation.

Model outputs closely resemble industry statistics. The average stocking rate is 1.3 per cent below the reported mean of 3.02 cows/ha for the Waikato region in 2008/2009 (Livestock Improvement Corporation, 2009). Average milk production is 4 per cent below the reported mean of 327 kg MS/cow for the Waikato region in 2008/2009 (Livestock Improvement Corporation, 2009). Mean nitrogen fertiliser use is 4 per cent greater than the regional average of 166 kg/ha in 2008 (Environment Waikato, 2008), while nitrate emissions are equal to the national mean reported by Basset-Mens *et al.* (2009). These close relationships give confidence that the model is broadly representative of farms in New Zealand's primary dairy region.

A lack of pertinent information means that the distribution of model output cannot be strongly validated. This is common in economic models, so validation is mainly focussed on inputs and model structure (McCarl 1984). Nevertheless, the model is judged to be a fair representation of the heterogeneity in the region following consultation with agronomists, the close equivalence between the mean values of each distribution and industry data, and the use of near-optimal solution space analysis (data not shown).

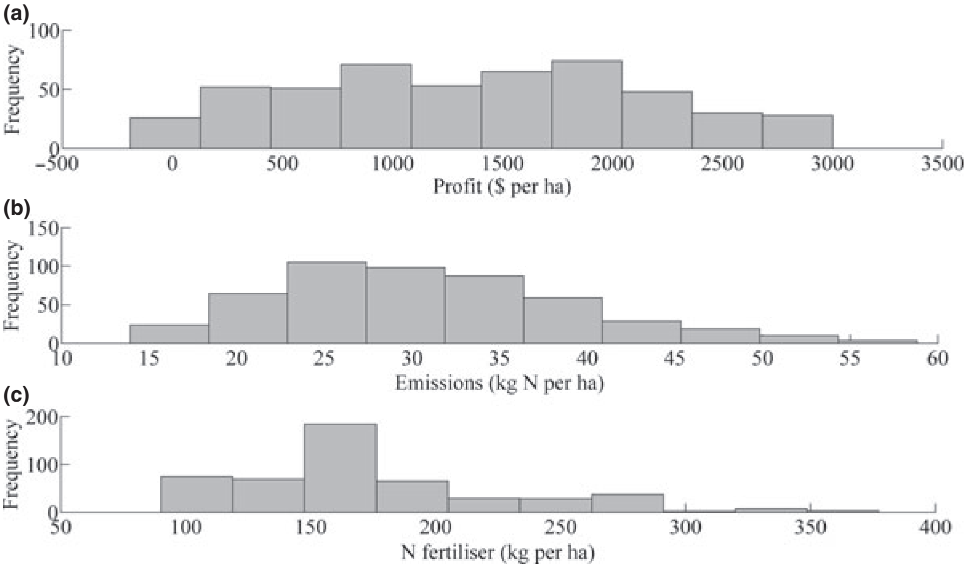

Figure 2 Probability distributions for (a) farm profit, (b) emissions, and (c) nitrogen fertiliser use from model output. Note that the histogram bin above the $0 per ha label on the x-axis in (a) contains a range of positive and negative values.

Table 1 Mean value of characteristics for farm cohorts sorted by level of baseline emissions (kg N/ha)

Characteristic	Baseline emissions per ha (kg N/ha)			
	0–24.46	24.461–29.81	29.811–36.06	36.061–58.97
Number of farms	124	125	125	124
Stocking rate (cows/ha)	2.44	2.81	3.08	3.6
Milk production/cow (kg MS/cow)	327	328	323	332
Milk production/ha (kg MS/ha)	798	922	995	1195
N fertiliser use (kg/ha)	126	152	173	238
Maize silage fed (t DM/ha)	0.79	1.21	1.56	2.48
N emissions (kg N/ha)	16.79	22.03	27.02	35.01
Farm profit ($/ha)	929	1252	1399	1863

Farms are sorted into four cohorts based on their N load without regulation. These are based on estimated quartiles for firm emissions. Table 1 reports mean values across optimal solutions for all farms within a given cohort. On average, the farms with higher emissions per ha possess a higher stocking rate, as the greater incidence of urine patches promotes N loadings. Higher stocking rates also increase the production of milk per ha and farm profit across the sample. More intensive farms use greater nitrogen fertiliser application and feeding of maize silage to support increased livestock intensity.

4.2. Abatement cost estimation

Table 2 compares the abatement costs identified in a model representing a single farm based on average values for all parameters (P1 in Section 2) and the catchment model involving heterogeneous firms with 498 distinct farms (P3 and P5 in Section 2). The representative farm model identifies broadly different abatement cost estimates for regulated decreases above 20 per cent. For example, abatement cost is around 20/25 per cent higher at decreases of 30/50 per cent in N load with the uniform policy in the multi-agent model. This difference occurs despite the representative farm model using the same data as the heterogeneous agent model. This example shows that ignoring farm heterogeneity in agri-environmental policy evaluation can lead to broadly different predictions.

Two policies are simulated in the heterogeneous farm model: one for a differentiated policy, in which abatement is targeted to low-abatement-cost farms (DP), and one for a uniform policy (UP), in which all farms are required to make the same percentage cuts. The differentiated policy always imposes a lower cost than a uniform policy because it optimally allocates abatement effort across farms and hence is the most efficient regulatory instrument (Table 2).

It appears that the cost savings from adopting a differentiated policy are likely to be small in this example (Table 2). A 30 per cent reduction over the catchment can be achieved at an annual cost of 3.3 million with a differentiated policy and 3.8 million with a uniform policy. A 50 per cent reduction over the catchment can be achieved at an annual cost of 12.2 million with a differentiated policy and 13.3 million with a uniform policy. Whether these cost differences are sufficient to outweigh the additional transaction costs of a differentiated policy would require careful consideration. The modest benefits reported for the differentiated policy is perhaps rather surprising given the

Table 2 Abatement cost per ha and over the catchment for different levels of regulated decreases in nitrate emissions for uniform policies in the representative farm model (RF), differentiated policies (DP) in the multi-agent model, and uniform policies (UP) in the multi-agent model

Decrease in N load (%)	Abatement cost per ha ($)			Abatement cost over catchment ($)		
	RF	DP	UP	RF	DP	UP
10	7	4	6	431 550	246 600	369 900
20	25	23	25	1 541 250	1 417 950	1 541 250
30	50	54	62	3 082 500	3 329 100	3 822 300
40	80	114	126	4 932 000	7 028 100	7 767 900
50	164	198	216	10 110 600	12 206 700	13 316 400
60	263	312	338	16 213 950	19 234 800	20 837 700
70	417	482	531	25 708 050	29 715 300	32 736 150

earlier evidence of substantial heterogeneity in this population of farms (see Figures 1 and 2). The reasons are explored further in Section 4.4.

Reductions of 30–50 per cent in nitrate load are required to satisfy Ministry for the Environment standards for water quality in the Waikato River (Vant and Petch 2006). Doole (2010) estimated that achieving a 30 per cent N reduction through differentiated standards for livestock intensity would cost around 16 per cent of profit, while a 50 per cent N reduction would cost 48 per cent of profit. These are substantially higher than the 4 and 14 per cent of profit it is estimated to cost here to achieve 30 and 50 per cent N reductions through differentiated emissions standards. The key reason is that this analysis incorporates additional CRMPs to those considered by Doole (2010), and these obviate the need for costly stocking rate reductions.

4.3. Responses of individual and catchment farms to regulation

Table 3 describes how a randomly selected firm in the catchment responds optimally to different N reductions enforced using a range of policies. A differentiated policy requires this firm to abate more than with a uniform regulation (Table 3). This infers that this farm has a shallower abatement cost curve than firms with lower emissions (see Section 4.4). This greater level of abatement with a differentiated policy incurs a greater cost on this farm, relative to a uniform policy (Table 3). Reduction in stocking rate is a key mitigation strategy across all policies, with greater reductions stimulated by more stringent regulation (Table 3). Nitrogen fertiliser application and maize silage

Table 3 Changes in N emissions associated with each mitigation strategy (kg N/ha/year), relative to standard management, for a randomly selected farm for 10, 30, and 50 per cent N reductions with a uniform policy (UP) and a differentiated policy (DP). For example, optimal management under a 10 per cent uniform regulation requires a stocking rate reduction that reduces N load by 2.27 kg N/ha/year. The farm has base profit of $798 and an unregulated leaching load of 45.53 kg N/ha

Item	N regulation and policy					
	10% UP	10% DP	30% UP	30% DP	50% UP	50% DP
Key farm output						
Farm profit ($/ha)	795	791	739	689	541	306
N abatement (kg N/ha)†	4.55	7.51	13.66	17.04	22.65	29.98
Mitigation strategies						
Stocking rate (cows/ha)	−2.27	−3.11	−4.92	−5.52	−8.89	−12.74
Milk production (kg/cow)	+0.04	+0.07	+0.1	+0.1	+0.16	+0.22
N fertiliser (kg/ha)	−1.57	−2.54	−3.77	−6.98	−10.55	−10.72
Maize silage (t/ha)	−0.38	−0.48	−0.71	−0.62	−0.93	−1.29
Dungbuster® system	−1.09	−2.43	−2.26	−2.03	−1.63	−1.42
Defer effluent application‡			−3.58	−3.21	−2.58	−2.24
Feed pad					−6.12	−5.31

†The abatement level is not the sum of the impacts of all mitigations listed given the impact of the constant term in the metamodel for nitrate leaching.

use also decline (Table 3). Additionally, milk production per cow increases as stocking rates fall; this increases N loads, but only to a minor degree.

Discrete mitigation strategies (ie CRMPs) are adopted in a stepwise manner as environmental regulations become increasingly stringent, as their cost is borne to offset costly decreases in livestock numbers (Table 3). Cheaper systems targeted at improving effluent management are employed at the 10 and 30 per cent regulations (Table 3). In contrast, reducing emissions by 50 per cent requires a proportion of the herd to be run on a feed pad over periods of high leaching risk. This practice is more expensive than improved effluent management, imposing increasing marginal abatement costs on the farm.

Table 4 describes how the farm cohorts – sorted according to baseline emissions – described in Section 4.1 respond to a differentiated standard set to achieve a 50 per cent reduction in N. Firms with the highest baseline emissions perform the most mitigation under a differentiated policy. This infers that it is less costly for these more intensive farms to do so. Nevertheless, farms with higher emissions practise a broader range of mitigation practices, which increases their total abatement cost (Table 4). Farms with greater emissions reduce stocking rate, nitrogen fertiliser application, and maize silage feeding by a greater amount than firms with lower baseline emissions, on average, with a differentiated policy (Table 4).

Table 4 Adoption of strategies to decrease N emissions with a differentiated policy set to achieve a 50 per cent reduction for farm cohorts sorted by level of baseline emissions (kg N/ha)

Characteristic	Baseline emissions per ha (kg N/ha)			
	0–24.46	24.461–29.81	29.811–36.06	36.061–58.97
Key farm output				
Abatement cost ($/ha)	117.68	169.9	221.69	264.83
N abatement (kg/ha)	5.29	7.92	10.85	13.36
Production intensity†				
Stocking rate (cows/ha)	−10.51	−12.71	−15.23	−13.78
N fertiliser (kg/ha)	−36.7	−38.84	−42.15	−48.19
Milk production/cow (kg/MS/ha)	+5.5	+5.97	+5.81	+3.91
Maize silage (t/ha)	−6	−13.35	−20.56	−22.79
Discrete mitigation practices				
Dungbuster® system	n = 498, MA = 100%	n = 498, MA = 100%	n = 498, MA = 100%	n = 498, MA = 100%
Defer effluent application	n = 498, MA = 100%	n = 498, MA = 100%	n = 498, MA = 100%	n = 498, MA = 100%
Feed pad	n = 90, MA = 78%	n = 89, MA = 77%	n = 87, MA = 78%	n = 87, MA = 80%
Nitrification inhibitors			n = 4, MA = 100%	n = 67, MA = 100%

†Production variable responses are reported as mean percentage changes. Adoption of discrete mitigations is summarised using the number of farms that use them (n) and the mean level of adoption on each farm (MA).

All cohorts adopt improved effluent management to reduce leaching load (Table 4). Moreover, each group feeds around 80 per cent of their stock on a feed pad over autumn–winter to reduce emissions. A number of farms with higher emissions also use nitrification inhibitors over all of their farms. This helps to meet leaching goals while promoting pasture production, allowing these farms to reduce nitrogen fertiliser application and the use of supplement. Nonetheless, nitrification inhibitors are not widely employed; for example, only 14 per cent of farms use them in the scenario reported in Table 4.

Table 5 describes how all farms respond to different N reductions enforced using a range of policies. Stocking rates, nitrogen fertiliser application, and maize silage use decrease significantly as more stringent regulations are required (Table 5). However, reported changes in key determinants of farm profit – stocking rate and nitrogen fertiliser application – are similar across differentiated and uniform instruments. The number of CRMPs and the level of intensity at which they are used increase as N must be reduced by greater amounts (Table 5). Moreover, the CRMPs used depend on the type of policy instrument employed, as uniform reductions require producers to adopt more expensive mitigation practices (nitrification inhibitors and feed pads), which may be avoided through the use of a differentiated policy (Table 5).

4.4. Relationship between baseline emissions and key model output

Abatement cost curves are estimated for each farm to identify the key source of the minimal differences between uniform and differentiated policies (Section 3.5). The cost savings achieved with a differentiated pollution policy, relative to a uniform instrument, are proportional to the coefficients of variation for baseline emissions per ha (a^j) and the slope of the abatement cost curve (c^j) (Newell and Stavins 2003). Baseline emissions differ (coefficient of variation of 0.28) given broad variation in stocking rates, nitrogen fertiliser application, milk production, and soil types. Slope parameters for firm-specific abatement cost curves (c^j) are widely distributed, with a coefficient of variation of 0.97. This variation suggests that differentiated instruments should be significantly more cost-effective than uniform policies.

Newell and Stavins (2003) outline that if firms responsible for the most mitigation possess shallower abatement cost curves (ie a^j and c^j are inversely correlated), then a differentiated and uniform policy will be closer in value. Under a uniform policy, firms with high baseline emissions per ha must abate more (in absolute terms) than firms with low emissions,[1] and they can do so more cheaply given that they possess shallower abatement cost curves, on average. This reduces the cost of a uniform standard, relative to the situation where a^j and c^j are not inversely correlated. In line with these arguments, the

[1] For example, a 20 per cent emissions standard imposed on two farms – one emitting 20 kg N/ha and one emitting 40 kg N/ha – will require the abatement of 4 and 8 kg N/ha, respectively.

Table 5 Adoption of strategies to decrease N emissions on all farms under different leaching targets and policy instruments for the catchment

Item	N regulation and policy					
	10% UP	10% DP	30% UP	30% DP	50% UP	50% DP
Production intensity†						
Stocking rate (cows/ha)	−2.54	−2.16	−6.63	−6.37	−13.49	−13.06
N fertiliser (kg/ha)	−8.37	−6.63	−53.85	−43.38	−73.18	−72.53
Milk production (kg/MS/cow)	+1.02	+0.79	+2.57	+2.49	+5.3	+5.17
Maize silage (t/ha)	−6.4	−5.65	−3.56	−4.6	−15.54	−15.68
Discrete mitigation practices						
Dungbuster® system	n = 496, MA = 98%	n = 498, MA = 100%	n = 498, MA = 100%	n = 498, MA = 100%	n = 498, MA = 100%	n = 498, MA = 100%
Defer effluent application	n = 203, MA = 15%	n = 0	n = 498, MA = 100%	n = 498, MA = 100%	n = 498, MA = 100%	n = 498, MA = 100%
Nitrification inhibitors	n = 0	n = 0	n = 16, MA = 32%	n = 0	n = 95, MA = 88%	n = 72, MA = 100%
Feed pad	n = 0	n = 0	n = 36, MA = 7%	n = 0	n = 479, MA = 62%	n = 352, MA = 78%

†Production variable responses are reported as mean percentage changes. Adoption of discrete mitigations is summarised using the number of farms that use them (n) and the mean level of adoption on each farm (MA).

cost savings achieved with a differentiated policy in this study are substantially dampened by a negative correlation between a^j and c^j ($\rho_{a,c} = -0.41$ and $\rho_{\ln a,\ln c} = -0.57$).

The distribution of abatement across farms is disparate for each policy instrument across a range of required reductions in N (Figure 3). A higher number of farms perform low levels of abatement under a differentiated policy, compared with a uniform policy. Additionally, a wider range of abatement is performed with a uniform instrument when regulation becomes more stringent, as more N must be mitigated (Figure 3). Abatement under a differentiated policy varies broadly from that attained with a uniform policy

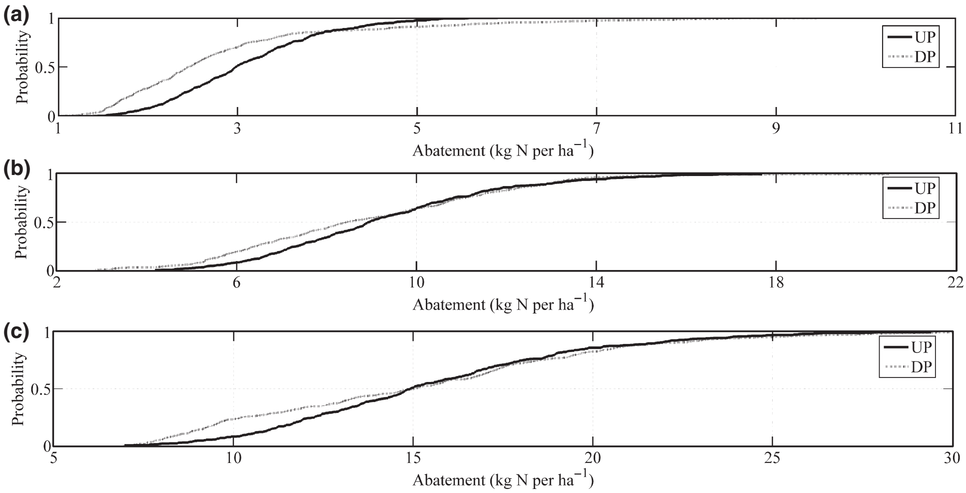

Figure 3 Cumulative probability distributions of absolute abatement performed on farms (kg N/ha) for a uniform policy (UP) and differentiated policy (DP) for a (a) 10 per cent reduction, (b) 30 per cent reduction, and (c) 50 per cent reduction in N load across the catchment.

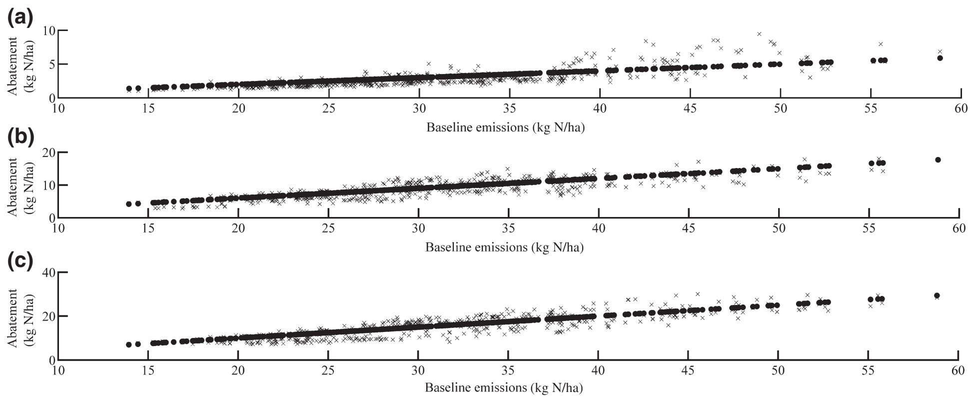

Figure 4 Absolute abatement performed on farms (kg N/ha) for a uniform policy (denoted by black circles) and differentiated policy (denoted by black crosses) for a (a) 10 per cent reduction, (b) 30 per cent reduction, and (c) 50 per cent reduction in N load across the catchment.

(Figure 4). However, firms with higher baseline emissions undertake more mitigation overall with the differentiated policy, similar to what occurs with a uniform regulation (Figure 4). This occurs because, on average, firms with high baseline emissions have shallower abatement cost curves and thus perform the most mitigation. This relationship is evident in that the correlations between c^j and the level of absolute abatement (kg N/ha) performed with 10, 30, and 50 per cent differentiated standards are $\rho = -0.33$, $\rho = -0.42$, and $\rho = -0.41$.

5. Conclusions

This study employs procedures for the calibration and decomposition of mathematical programming models to explicitly consider firm heterogeneity in agri-environmental policy evaluation. This approach is used to assess differentiated and uniform standards for regulating nitrate emissions from intensive dairy production in New Zealand. The model incorporates over 3 million constraints and hence describes significant heterogeneity between 498 farms.

The estimated mitigation costs increase with greater abatement, but under optimal management, the costs are generally modest: 4 or 14 per cent reductions in profit to achieve 30 or 50 per cent N reductions with differentiated emissions standards. A differentiated policy instrument results in cost savings relative to a uniform standard, but in this case study, the difference in costs is not large (15 and 9 per cent for nutrient reductions of 30 and 50 per cent, respectively). These cost savings from a differentiated policy could easily be outweighed by the associated administration costs. The reason for the modest difference is that, in this example, there is a negative correlation between baseline emission levels and marginal abatement costs. A uniform policy has the largest impact on those farms with the highest baseline emissions, but in this study, those farms also have the lowest marginal abatement costs, so they also perform the greatest emission reductions under the differentiated policy. Thus, the difference in efficiency between the two strategies is not as large as it would be if the slopes of firm-specific abatement cost curves were unrelated or positively related to baseline emission levels.

We found that a representative farm approach to modelling compliance costs underestimated abatement costs in this case study, indicating the value of representing multiple agents in policy models where sufficient data are available. Interestingly, it may be worthwhile representing inter-farm heterogeneity in the analysis, even if the benefits of a differentiated policy are low.

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Supporting Information

Additional Supporting Information may be found in the online version of this article:

Data S1. The equations used in the individual farm models incorporated in the catchment analysis model.

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