# The Spatial Distributional Effect of Common Agricultural Policy Reform

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**Abstract.**

Agricultural incomes are quite heterogeneous relying as they are in part on the environmental context which land is farmed. In addition a very significant proportion of agricultural income results from public policy via the Farm Direct Payments within in the Common Agricultural Policy. In this paper we develop and test a methodology to spatially model the distribution of Agricultural Activity and associated income across place utilising a spatial microsimulation model. In particular we build upon a quota sampling method used in the development household based spatial microsimulation models to account for spatial heterogeneity in relation to stocking rate. We utilise this framework to model the spatial distribution of activity, incomes and viability across Ireland. We also model the static spatial incidence of changes in the Common Agricultural Policy.

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**The Spatial Distributional Effect of Common Agricultural Policy Reform**

## 1. Introduction

While the overall contribution of the agri-food and bioeconomy sector in Ireland to net export earnings is very high (Riordan, 2012), the primary agricultural sector remains highly reliant on subsidy income (O'Donoghue and Hennessy, 2014) as typically about 65% of factor income comes in the form of subsidies, largely coming from the Common Agricultural Policy. These payments are thus very important in maintaining the viability of the primary agricultural sector on which much of the wider sectoral returns are based.

There are considerable differences in the reliance on subsidies across the various farm sectors, with the dairy and the tillage sectors that consistently returns a market based profit. These sectors are the only consistently profitable systems based upon net margin (market sales minus direct and overhead costs), with other sectors relying on subsidies to produce a positive family farm income (net margin plus subsidies). For example The net margin per hectare for the specialist Dairy sector in 2010 was €600 per hectare higher than the next system (mixed Dairy and Other) and over €700 more than the next non-dairy system (O'Donoghue and Hennessy, 2014). There is a relatively substantial literature on the distributional consequences of agricultural policy change (Keeney, 2000; Allanson, 2006; Allanson and Rochi 2008; Alfaro-Navarro et al., 2011; El Benni et al., 2012; Severini and Tantari, 2013), however the spatial incidence is limited.

The is significant spatial heterogeneity in Agriculture. For example soils, weather and other agronomic conditions vary across space influencing yields and agricultural outcomes and concentrations. Spatial location may influence policy related subsidy payments such as historical production related single farm payments which in turn are partially a function (positively ) of agronomic conditions, while conversely less favoured area payments are negatively correlated with agronomic conditions. There may in addition be specific agri-environmental payments associated with farming in areas of high nature value or special areas of conservation. For this reason it is useful to be able to capture this spatial heterogeneity when undertaking an analysis of policy change in relation to agriculture

For the purpose of the analysis in this paper, there is significant spatial heterogeneity in agriculture in Ireland (See Crowley et al., 2008), with by and large the better land in the South and East and the poorer land in the North and West (See Frawley and Commins, 1996). The most profitable sub-sectors within agriculture, dairy and to some extent tillage farming, are predominantly concentrated in the South and East. The lower margin beef and sheep sectors are to a large extent located in the Midlands, North and West of the country. It is important to understand this spatial heterogeneity so as to be able to better target policy interventions. In particular the spatial distribution of Agricultural income and the consequential impact of policy reform such as CAP reform are important in targeting for example agricultural extension resources or the development of localised rural development interventions.

The challenge in understanding the spatial distribution of farm incomes and of associated policy reform is one of data. Administrative data often lack contextual information when simulating the spatial pattern of farm direct payments, limiting the depth of analysis possible (See Bergmann et al., 2011 at a spatial scale in Scotland and Donnellan et al, 2013 at an aspatial scale in Ireland). Typically Censuses of Agriculture and Administrative data provide spatial information on the structure of agriculture, but have no income or farm structure data. On the other hand Farm Accountancy Data Network (FADN) type data contain excellent farm income and structural data, but have weak spatial dimensions. Finger and El Benni (2011) undertook a spatial incidence of agricultural payments in Switzerland, but the spatial level of disaggregation was limited to the canton or regional level. Intra-region heterogeneity however can be significant and as a result it is of interest to attempt to disaggregate at a more refined spatial scale. Data imputation/enhancements methods using (O'Donoghue et al., 2014; Hermes and Poulsen, 2012) however have been developed for to combine the strengths of both types of data.

There is a growing field of spatial microsimulation modelling in Agriculture. Hynes et al. (2009b) used a model of spatial farm incomes to examine the impact of EU Common Agricultural Policy Changes historically (Hennessy et al., 2007). This methodology has also been applied in other countries such as Van Leeuwen et al. (2008) in the Netherlands. These methods involve resampling or reweighting farm survey data to be consistent with spatial calibration totals.

We utilise the spatial distribution of agricultural incomes within a spatial microsimulation model of Irish Agriculture (O'Donoghue et al., forthcoming) the resulting to analysis the spatial impact of the proposed CAP reforms in Ireland in the post 2014 period. The paper concentrates in particular on the changes to the CAP Pillar 1 payments as this payment forms the large majority of direct payments to farmers.

This paper is structured as follows. We present the policy context to this paper in section 2. Section 3 describes the methodological framework for modelling the spatial distribution of income. In section 4 we discuss the preparation of the data and some summary statistics. Subsequently we report results the spatial impact of the CAP.

## 2. Policy Context

Agricultural Policy is a policy area largely determined at the European level via the Common Agriculture Policy (CAP). Its original objectives were to increase agricultural productivity, ensure a fair standard of living for the agricultural community, to stabilise markets, to assure the availability of supplies; and to ensure that supplies reach consumers at reasonable prices (Oskam et al., 2011).

The mode of operation has changed over time.

- Prior to 1992, the main instruments of the CAP to achieve its objectives were market related instruments aimed to control quantities of supply and price. These included the use of quotas, using setaside land, Levying import levies or quotas on imports, the use of price floors, a price maintenance mechanism based upon the target, threshold and intervention prices etc.
- Over time, these policies resulted in over production, severe budgetary pressures, pressures from trade partners as part of the GATT/WTO Uruguay round, which resulted in a series the reforms that took place in 1992, known as the MacSharry reforms in 1992. The objective of these reforms was to introduce

a set of direct payments to compensate farmers for the reduction in direct market supports. Although these instruments were mainly introduced post 1992, a number of premia payments as they were known were introduced in 1980's, including suckler cow premium in 1980 and a ewe premium in 1989 (Frawley et al., 2000).

- The Berlin Agreement in 1999 reduced support prices for agricultural beef, cereal and dairy commodities.
- There was a significant reform in 2005 following the entry of the new member states from Eastern Europe and the Mediterranean in 2003 (Pirzio-Biroli, 2008) in relation to the decoupling of farm support payments, utilising a variety of methods including the historic method produces which depended upon historical production levels, regional flat payments where farmers received the same rate per hectare as all other farmers in the same region, a hybrid approach which combines both. Ireland selected the historic payments method.

As part of the EU budgetary reforms in 2013, further changes are being proposed to the CAP to reduce the cost of the programme, to target a number of behavioural changes such improving the environment, incentivising young farmers, supporting small farms and those with poor agronomic conditions and reducing anomalies where payments were based upon production from more than 10 years earlier. The proposed new CAP contains seven programmes of which 3 are compulsory; Basic Payment Scheme (BPS), the Greening Payment Scheme (GPS) and the Young Farmers' Scheme (YFS).

The objective of the BPS is to converge on a national or regional average payment level by 2019. However member states can choose to implement an internal convergence model where payment levels converge on but do no reach a common rate by 2019. Under this latter model, where an initial unit value of entitlement is less than 90% (or 100%) of the national average, this unit value is increased by at least 1/3 of the difference between the initial unit value's level and 90% of the average level (or 100% of the average level) by 2019 (Donnellan et al., 2013). Member States must also allocate at least 30% of their direct payments budget to the GPS and paid either on a flat basis or in proportion to the GPS. While the YPS is compulsory, new minimum payment has been mandated. Rather a maximum of proportion of 2 per cent of total payment is set. The four optional programmes, which also have maximum payment shares are

- voluntary coupled support scheme (VCSS),
- the redistributive payments scheme (RPS),
- the areas of natural constraint scheme (ANCS) and
- the small farmers scheme (SFS)

Hennessy and Hanrahan (2013) have undertaken a distribution analysis of a range of options for Ireland, considering a variety of coupled and redistribution strategies. The main findings are that in general, greater numbers of farmers gain under options where some coupling of suckler cow and ewe payments are included. However, in general the income changes (gains and losses) are less than 10 per cent. Their results suggest that those farms that gain from the coupling of direct payments to production tend to account for a smaller proportion of output than those that lose, with a significant proportion of farm output being generated by farms that lose significantly from the higher rate of decoupling.

Given the spatial pattern of Agriculture, we would expect a spatially asymmetric impact of these reforms. Consequentially, we will consider the impact of the reforms in changing the spatial distribution of incomes, whether they are reducing or increasing spatial inequality. Secondly, we would like to consider the impact of within area heterogeneity, so even if a particular area has a net gain, are there also losers within these areas..

## 3. Methodology

Given a lack of spatially disaggregated farm survey data, the objective of the methodological exercise in this paper is to create a synthetic spatial farm dataset, combining the best of both farm level survey data and spatially disaggregated Census of Agriculture data.

Small area statistical analysis can be used for this purpose (See Ghosh, 1994). However for our purposes, we are interested not only in inter-spatial variation in incomes but also intra spatial area variation of incomes. Therefore we require a method that maintains both spatial variability and micro-level variability.

Spatial microsimulation (Clarke, 1996) is a potential methodology achieving both of these dimensions within its data enhancement process. There is an extensive literature described in O'Donoghue et al (2014) covering many different policy areas, utilising various methodologies described in Hermes and Poulsen, 2012.

The methodology has been applied in a number of instances within agriculture and rural development. (Ballas et al., 2006) utilised iterative proportional fitting to examine CAP reform as part of the Luxembourg agreement. Hynes et al. (2009b) developed a model of spatial farm incomes utilising simulated annealing, which has been used to examine the impact of EU Common Agricultural Policy Changes (Hennessy et al., 2007). This forms part of the Simulation Model of the Irish Local Economy (SMILE) (O'Donoghue et al., 2013). O'Donoghue (2013) extended the farm focused models to include wider household income sources to be able to assess the wider economic sustainability of farm households. Clancy et al. (2013) utilised the model in Ireland to assess the optimal spatial location for the growth of willow and miscanthus for biomass production. Lindgren and Elmquist (2005) linked natural sciences and economics in their Systems AnaLysis for Sustainable Agricultural production (SALSA) model to evaluate the economic and environmental impact of alternative farm management practices on a site specific arable farm in Sweden.

A variant of the agricultural dimension of SMILE (Hynes et al.,2009b), focuses on recreational activity in forests within a single city (Cullinan et al., 2008). Also with a small area focus (a number of municipalities), van Leeuwen et al. (2008) have developed a model exploring the linkages between on and off-farm employment, which is becoming an increasing part of farmer's incomes in the EU. While there have been many examples of aspatial static microsimulation models that have simulated greenhouse gas emissions, the spatial models that have modelled these emissions tend to be those where spatial context is relevant such as agricultural models (Hynes et al., 2009a), land use (Moeckel et al., 2007) or transportation issues (Mavoa, 2007). In terms of environmental and biodiversity related issues, microsimulation models were used to look at a range of issues including wildlife-recreation interaction (Bennett et al., 2009) and the non market value of wild bird conservation (Hynes et al., 2010), landscape services from Agriculture (Pfeiffer et al., 2012) and participation in Rural Environmental Protection Schemes, (Hynes et al., 2008).

In order to undertake a spatial impact analysis of the CAP reform, we need to statistically combine farm level survey data, Teagasc National Farm Survey (NFS), the Irish version of the Farm Accountancy Data Network.with spatial Census of Agriculture data. The most recent Census of Agriculture was collected in 2010 and released for research purposes in 2013 (CSO 2010). We wish to combine this with the 2010 Teagasc National Farm Survey.

O'Donoghue et al. (forthcoming) and Hermes and Poulsen (2012) describes a number of potential methodologies to do this. Potential options include

- Iterative Proportional Fitting
- Deterministic Reweighting
- Combinatorial Optimisation
- Quota Sampling

In determining the methodology to use for the creation of a farm level spatial microsimulation model, we faced a number of issues. While Iterative Proportional Fitting (Ballas et al., 2006) could potentially be used to produce small area weights, it struggles to deal with the issue of heterogeneous stocking rates. As the survey has a greater sample size than the cell size for most districts, resulting in weights of less than 1, it is likely that this approach will smooth the heterogeneity of farm incomes. Similarly given how many districts have small numbers of farms in Ireland, the GREGWT reweighting method (see Tanton et al, 2011) used in household analysis Australia is potentially challenging and may smooth incomes. Simulated Annealing (SA) was used to generate an earlier version of the model (Hynes et al, 2009) but has significant computational costs and also struggles with the heterogeneous stocking rate issue.

Thus we were motivated to develop a methodology that was sample based to avoid the income smoothing concern of the weighting methodology, was computationally efficient and could be adjusted to improve the spatial heterogeneity of stocking rates.

We have thus developed in parallel with Farrell et al. (2013) a method known as Quota Sampling (QS) which is a probabilistic reweighting methodology developed which operates in a similar fashion to Simulated Annealing (SA) (Wu and Wang, 1998), whereby survey data are reweighted according to key constraining totals for each small area, with amendments made in the sampling procedure in order to improve computational efficiency. We call the resulting model SMILE-FARM[2]. The basic sampling procedure, and its implementation in the overall simulation process, is now outlined.

Similar to SA, quota sampling selects observations at random and considers whether they are suitable for selection for a given small area based on conformance with aggregate totals for each small area characteristic. Unlike SA, Quota Sampling only assigns units (in this case farms) that conform to aggregate constraint totals and once a unit is deemed selected, it is not replaced; the main computational improvement.

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[2] SMILE-FARM: Simulation Model of the Irish Local Economy, Farm Model

The quota sampling process involves the following steps

- Thus for each unit *i*, we draw a random number *v*
- Sort units by *v*.
- Select the unit for spatial sample if $x_{j,s}^{acc} + x_{j,i} \leq x_{j,s}^{total} \forall j$, where $x_{j,i}$ is the value of the variable j for the unit i, $x_{j,s}^{total}$ is the target total for district s for variable j and $x_{j,s}^{acc}$ is the running total for variable j for district s.
- If $x_{j,s}^{acc} + x_{j,i} > x_{j,s}^{total}$ for any j, then the we do not sample the unit i.

Thus, one can see that the variation of admitted units cumulates in a random sort which is consistent with aggregate constraint totals. This mechanism of sampling without replacement avoids the repeated sampling procedure of SA and is fundamental to the efficiency gains of the quota sampling procedure relative to other methods. One can see that the process is analogous to the type of quota sampling undertaken by market researchers, whereby only individuals considered relevant to concurrent quota counts are admitted to a sample.

This method of improving efficiency does present a number of convergence issues, however. Disparities in population distributions between census and survey totals may create a number of problems for unit-based microsimulation procedures. This is because survey microdata are representative at the national level, whereas small area census data are representative at the district level. This poses little difficulty in simulating small areas that have a population distribution similar to that of the national distribution, but areas that differ from the national distribution may lead to some demographic groups consistently being underrepresented in a given district. These differences may cause some districts to consistently fail in reaching adequate convergence.

Also, the use of sampling without replacement in quota sampling results in quota counts becoming increasingly more restrictive as the simulation progresses. As quota counts reach their target, the search space is continuously refined in accordance with concurrent quotas, whereby all units no longer eligible given updated quota totals are removed from the subset and the procedure is repeated[3]. When each constraint allocation reaches its target quota, all individuals of that characteristic are removed from the candidate search space. These mechanisms cumulate to offer a continuously diminishing search space and may prohibit convergence, whereby no unit is able to satisfy all concurrent quota counts.

*Improving the fit of the Spatial Stocking Rate*

Hynes et al. (2009) utilised farm size, farm speciality and soil code to generate the spatial distribution of agriculture. This however ignores differences in stocking rate, which given that that Irish Agriculture is largely animal based is likely to be a significant driver of farm income heterogeneity not accounted for by farm system, size and soil type. In addition to economic considerations, it is also likely to be an important driver of the environmental impact of agriculture.

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[3] e.g. with a remaining quota count of *n* individuals of class *k* to be filled, the search space is refined to exclude households containing *n+1* individuals of class *k*.

While we know the average stocking rate in each spatial district and we know the stocking rate of each farm, we are unable to utilise this variable within the quota sampling process or the Simulated Annealing process, which requires the number of farms with a particular characteristic to be sampled. These methods cannot handle spatial averages.

Thus the objective of this new methodology is to improve the spatial heterogeneity of the stocking rate. In devising a method, consider the following relationship between match variable (soil, system, size) dummies and stocking rate

$$stocking\_rate_s = \sum_j match\,\mathrm{var}\_share_j \beta_j + u_s \tag{1}$$

Where the stocking rate of the district s is a function of the share of farms by system, farms by size and farms by soil type, with unobserved heterogeneity being accounted for by a stochastic term $u_s$

Consider now the stocking rate for farm i

$$stocking\_rate_i = \sum_j match\,\mathrm{var}\_share_j \beta_j + u_s + \varepsilon_i \tag{2}$$

where the stocking rate of the farm i is a function of the share of farms by system, farms by size and farms by soil type, with spatial unobserved heterogeneity $u_s$ and farm level unobserved heterogeneity being accounted for by a stochastic term $\varepsilon_i$.

Thus if we believe in the consistency of our spatial and survey data, where by the underlying relationship between the stocking rate and match variables are the same, then rather than randomly selecting farms for selection, we would like to select farms where the unobserved heterogeneity is similar.

We can partially identify this by estimating $\beta_j$ using our spatial data and deriving an area effect $u_s$, applying the coefficients $\beta_j$ to the micro data and deriving farm level unobserved heterogeneity $u_s + \varepsilon_i$. A selection of farms that can result in a similar spatial stocking rate from sampling to the actual spatial stocking rate are farms farm level unobserved heterogeneity $u_s + \varepsilon_i$ is closest to the spatial unobserved heterogeneity $u_s$.

To improve the fit, therefore rather than sorting randomly, we sort on the difference between the two residuals. Thus, before selection commences, farms are ranked by the smallest absolute difference between the stocking rate residual for the current district and the stocking rate residual contribution reported for the sample farms. This step means that farms with residuals which most closely resemble the residual stocking rate of the target district are more likely to be selected first. The SMILE-FARM model then considers each ranked farm in the micro data file for inclusion in target district. The application of this ranking is designed so that each target Districts residual stocking rate, unexplained by the linear regression model, can be somewhat preserved.

This assumption rests on the basis that if spatial unobserved heterogeneity is important then $u_s$ is high as a share of $u_s + \varepsilon_i$ in which the approximation of the absolute difference between the residuals will largely account for the spatial effect. On the other hand if unobserved spatial heterogeneity is small, then the absolute difference will be largely driven by the aspatial stochastic term which is assumed to be random.

## 4. Data and Validation

In this section we discuss the data required for our analysis and provide some summary statistics. In designing a framework for spatial microsimulation models, the basic goal is to ensure that units from the micro data are simulated to the destination spatial unit by matching the characteristics of the micro units selected to the spatially heterogeneous characteristics of the spatial unit.

*Data Description*

In the SMILE-FARM model, farms from the Teagasc National Farm Survey (NFS) 2010 are sampled to reflect the structure of an Electoral Division (ED) on the basis of aggregate farm totals reported for that district in the Census of Agriculture (CoA) 2010.

Teagasc's National Farm Survey (NFS) to describe the distributional and incentive implications of the SFP. The NFS is collected as part of the Farm Accountancy Data Network of the European Union (FADN 2005). It determines the financial situation on Irish farms by measuring the level of gross output, costs, income, investment and indebtedness across the spectrum of farming systems and sizes (Connolly et al. 2010). A random sample of approximately 1,200 farms is surveyed each year.[4] In the Teagasc National Farm Survey (NFS), the principal measure of the income which arises from the year's farming activities is Family Farm Income per farm (FFI). The FFI is calculated by deducting all farm costs (direct and overhead) from the value of farm gross output and adding farm subsidises. Farm Gross Output (GO) does not include income from non-farming sources and thus may not be equated to household income. Most farms in Ireland contain multiple enterprises (beef cattle, sheep, dairy cows, cereals etc.) and so the National Farm Survey classifies a farm by the dominant enterprise. The dominant enterprise is defined as the system with the highest share of gross margin (output for the enterprise minus direct costs). There are substantial variations in margins across enterprises.

The Census of Agriculture is collected approximately every 10 years. It collects primarily physical data in relation to the number of animals by type, the size of the farm and the land use on the farm as well as some demographic data. The objective of the Census was to identify every operational farm in the country and collect data on agricultural activities undertaken on them (CSO, 2000). The scope of the census was all farms, where the agricultural area used for farming was at least 1 hectare. The census classifies farms by physical size, economic size, economic type and geographical location. Due to the Commission decision 78/463ECC all the farms covered in the 2010 Census of Agriculture are classified down to the most detailed farm system classification (Projet de Decision de la Commission, 1992). However, as

[4] Very small farms, and pig farms are excluded.

many of the farm system types present in the Commission decision 78/463/EEC are not used in Ireland, five summary farm type classes of general interest to Irish agriculture were selected from the EU typology as follows (Census of Agriculture, 2000): Specialist Tillage, Specialist Dairying, Specialist Beef Production, Specialist sheep, Other. It contains information on approximately 139,000 active farms (CSO, 2010).

Hynes et al. (2009) identify limitations associated with the NFS and the Census of Agriculture. The NFS contains a large amount of information on farming activity but is only nationally representative and cannot be used for analysis at the local level. On the other hand, the Census of Agriculture has limited individual farm information and some information is unavailable due to confidentiality issues. It does however have information on a small number of key farm variables at a very local level (ED). Therefore, while neither the Census nor the NFS alone provides policy-makers with a complete overview of all of the important farming activities and attributes at the local level, if combined to form a static farm level spatial microsimulation model the resulting dataset would provide policy-makers with detailed synthetic microdata as to inform their decision-making at a spatially disaggregated level.

*Validation*

We consider a a number of methodological choices when undertaking the data enhancement methodology in producing the spatial distribution of Agricultural Income. These choice include

- Sample from with farms within the same region or from the national sample in the National Farm Survey
- Sample within Less Favoured Areas or not
- Sample randomly or adjusting for localised stocking rate

The first set of choices relate to the sampling frame that is used in the data enhancement process. One can choose to sample from the entire NFS sample or from a subset such as the 8 NUTS3 regions. Sampling from a relevant subset such as only sampling farms from the Western region when generating data for Western region districts allows for some spatial heterogeneity to be preserved, recognising for example that beef farms that are selected are more likely to be suckler farms in the West and Cattle rearing farms in the East. However sampling from a smaller spatial unit can result in a smaller cell size which may result in greater difficulties in achieving convergence. However this may come at the cost of a smaller cell size.

A slightly more aggregated sampling unit is to sample separately for less favoured areas that comprise over 70% of farms and non less favoured areas. It has some advantage in enhancing heterogeneity without as much sample size constraints.

The standard method involves ranking farms randomly and then selecting until quotas are filled. An alternative is to utilise the alternative ranking method described above, where farms are ranked on the absolute difference in residuals. A fourth choice is the post sampling regional fixed effect adjustment described above.

In this section we test the performance of a number of different options as follows. Table 1 describes the nature of the 6 potential options. We do not consider both sampling within Less Favoured Areas and within region in the same scenario.

**Table 1. Methodological Scenarios**

| Scenario | 101 | 111 | 0 | 10 | 100 | 110 |
|---|---|---|---|---|---|---|
| LFA sub-group | 1 | 1 | 0 | 0 | 0 | 0 |
| Stocking Rate Adjustment | 0 | 1 | 0 | 1 | 0 | 1 |
| National (1)/Regional(0) Sample | 1 | 1 | 0 | 0 | 1 | 1 |

**Table 2. Correlation of Winners and Losers by Region – SMILE vs NFS**

| Mode | 101 | 111 | 0 | 10 | 100 | 110 |
|---|---|---|---|---|---|---|
| Average Constraint | 0.937 | 0.940 | 0.884 | 0.890 | 0.937 | 0.940 |
| *No LU per ha* | 0.397 | 0.861 | 0.411 | 0.681 | 0.397 | 0.861 |
| *CAP Reform* | | | | | | |
| Winners | 0.36 | 0.38 | 0.99 | 0.96 | 0.36 | 0.38 |
| Losers | 0.61 | 0.44 | 0.98 | 0.95 | 0.61 | 0.44 |
| *Earlier validation* | | | | | | |
| No. LU per Ha | 0.39 | 0.86 | 0.41 | 0.68 | 0.39 | 0.86 |
| Av. Constraints | 0.94 | 0.94 | 0.88 | 0.89 | 0.94 | 0.94 |
| *Average* | *0.57* | *0.65* | *0.82* | *0.87* | *0.57* | *0.65* |

Note.

1. The “min” scenario is used in this simulation
2. Model is defined as LFA sub-group + 10*Stocking Rate + 100* National Sample + 1000* Regional Fixed Effect Adjustment
3. Winners and Losers are characterised by those who respectively gain or lose by 10% or more relative to previous single farm payments

The SMILE-FARM match for 2010 achieves the target total number of farms for all districts. In order to test the effectiveness of each match, we report the averate correlation between the raw and sampled constraint variables (soil, system, size) and with the non constraint variable stocking rate per hectare in Table 2.

Utilising a national sample relative to a regional sample has the biggest improvement in the average correlation, increasing the fit by about 5 percentage points. This is due to the fact that when we use the national sampling frame, the cell sizes are larger, giving the algorithm a wider choice of farms from which to select.

Amongst the other choices, there is a marginal improvement as the algorithm becomes more sophisticated with the stocking rate adjustment, selection from within relevant Less Favoured Area category and regional error adjustment. However these marginal changes are small relative to the impact of the national/regional sampling choice.

Given the importance of animal systems in Irish Agriculture, the performance of the selection relative to the actual district stocking rate is important. Here we find a substantial difference in the performance. Selection scenarios that do not make the stocking rate adjustment are poorer with correlations typically 0.4 or lower than those that make the adjustment. The best performing scenarios are those with a stocking rate adjustment, with a national sample at about 0.85 correlation. Again there are marginal improvements with the regional error adjustment for the national sample, but a reduction for the less favoured area selection. The performance of the national sample is slightly better than when we select from within a less favoured area. When we select from within region with a stocking rate adjustment, the correlation is about 0.7

The nature of the match-process is such that there is a trade off b/w methodological complexity and computational efficiency. While it is possible a more accurate match for the match variables may have be obtained using the previous simulated annealing method developed by Hynes et al, (2008) the computational cost of simulated annealing approach is high. The quota sampling method provides a high level of accuracy for the match variables and allows the simulation to be modelled in a number of hours. The inclusion of a ranking mechanism provides the added benefit of preserving much of the spatial heterogeneity of each districts stocking rate.

The objective of this paper is to model the distributional impact of CAP pillar 1 reforms. Donnellan et al., (2013) modelled the distributional impact at a national level using the National Farm Survey. It is however possible to disaggregate this analysis by region, which is a useful validation at a regional level with the analysis here. One of the main analyses in Donnellan et al., is the classification of winners and losers of more than 10% of their single farm payment. This statistic depends upon the distribution of original single farm payments, which is in turn a function of both historical farm systems and production levels and intensities. As some of this information is not directly sampled a validation of the share of winners and losers is quite a tough challenge for the model.

In this analysis, we choose the Min scenario which is equivalent to the choice made by Ireland from amongst the possible scenarios; essentially where none of the optional choices were made, thus where 70% of the payment would be made in terms of the Basic Payment Scheme (BPS), and 30% paid via the Greening Payment Scheme (GPS) and a minor Young Farmers' Scheme (YFS).[5] We ignore here any changes to CAP pillar 2 as they structure of these schemes have not been identified yet.

The first part of Table 2 reports the correlations of regional shares of winners and losers (more than 10%). The rankings of validation performance is quite different to the comparison with Census constraint variables and with the local stocking rate. In this case only the regional sampling scenarios, with and without stocking rate adjustment (10, 0) perform satisfactorily. In general the correlation of losers is better than winners. The worst performing scenarios are those in which we undertake a regional adjustment, as this is distorting the national distribution of incomes and single farm payments. While the national sampling scenarios are less bad in general, we find that they do not reproduce the regional variability of single farm payments observed in the regional sampling scenario.

Our choice of "optimal" scenario is therefore a multiple criteria decision. From this perspective, the best choice is choice 10 (stocking rate adjustment with regional sampling). This is not the best choice on any of the specific criteria but combines a strong performance on the CAP validation, with very good constraints and good stocking rate correlations. However, depending upon the purpose of the analysis, a different sampling scenario choice may be best.

*Spatial Pattern of Agriculture*

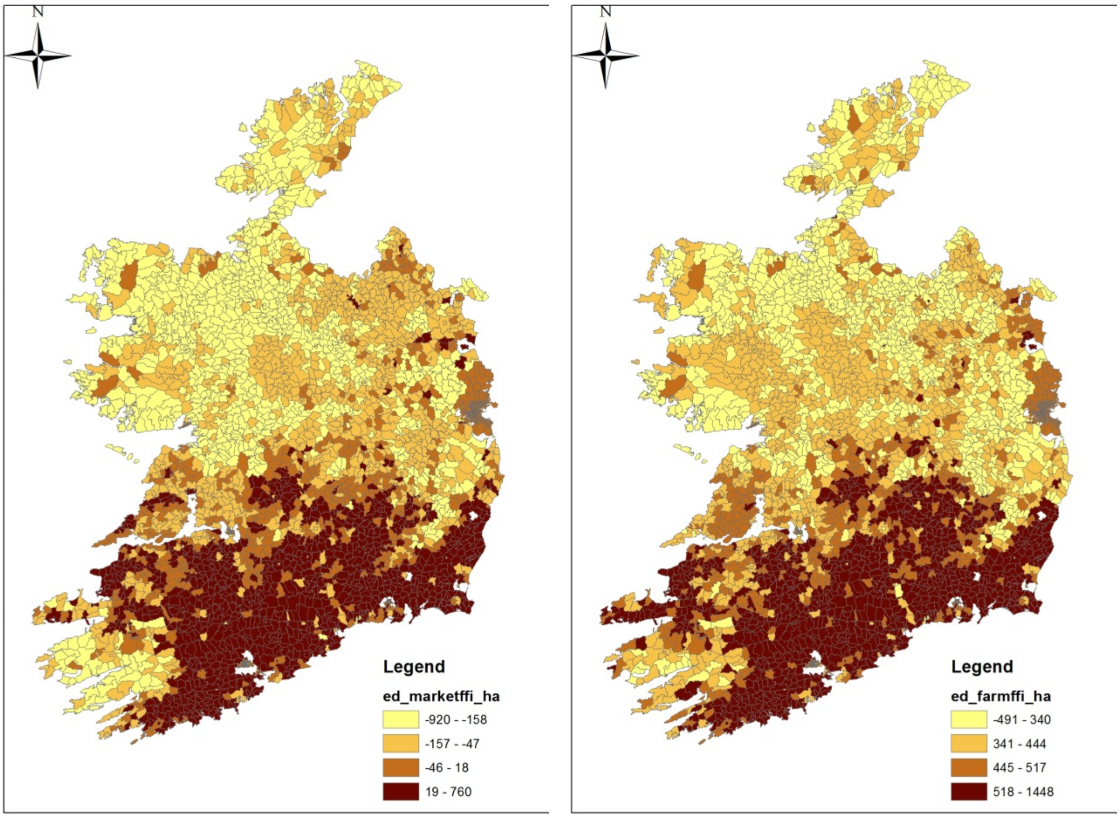
The Teagasc National Farm Survey in 2010 (Hennessy et al., 2011) reported that specialist dairy enterprises had an average income from farming (and subsidies in

[5] The YFS is not modelled here as it is not possible to identify recipients in the data. However the spatial impact is unlikely to be significant.

brackets) of €44432 (€21255), compared with €7023 (€13574) from cattle rearing enterprises, €12269 (€16528) from specialist sheep enterprises and €26759 (€24791) from specialist tillage enterprises. Thus as we can see, there is both a significant variability in incomes, but particularly so in net income from the market, defined as income minus direct payments which are dairy (€23177), beef (-€6551), sheep (-€2259) and tillage (€1962). Thus cattle and sheep enterprises are loss making from the market, relying on subsidies for income sustainability, while, dairy and tillage farming is largely profitable. Thus the spatial pattern of income will depend significantly on the predominance of these activities in particular locations.

**Figure 1. Farm Incomes**

| (a) Market Family Farm Income per Ha | (b) Family Farm Income per Ha |
|---|---|




Source: SMILE-FARM 2010

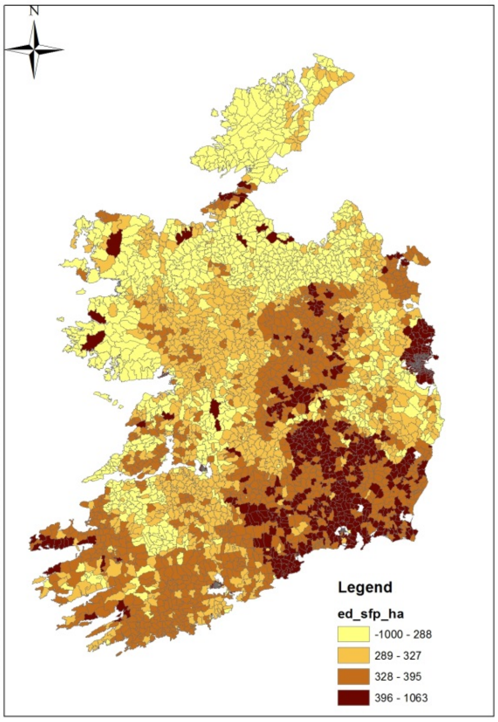
In this section we will describe the spatial structure of Agriculture observed in our synthetic population. Figure 2 describes the pattern of, market farming income from farming (excluding a return to labour or land) per hectare, direct payments per hectare and their sum family farm incomes per hectare. Market Income from farming reflects the location of dairy and tillage farming in the South and East and corresponds to the better land and consistent with the Commins-Frawley line from Dundalk to Limerick (Frawley and Commins, 1996) which divides what are effectively two agricultural economies. The spatial pattern of direct payments is less clear cut. While the pattern of single farm payments will be a function of particularly the intensity of cattle production and tillage production, largely down the East coast, the prevalence of disadvantaged area payments and agri-environmental payments will typically be more likely to be on the West and in the North in poorer agronomic zones. Combining the two measures, we find that market income driving the overall pattern.

## 5. Spatial Impact of CAP Reform

In this section, we analyse the spatial distributional impact of CAP reform, modelling the Min scenario from above, without a redistributive or coupled component. It should be noted that we only model changes to Pillar 1, holding pillar 2 constant. From the perspective of the local economy, it is important that we can identify the parts of the country that would be worst affected by the decline in the single farm payment. Figure 3 describes the spatial pattern of payments in the Baseline and Reform scenarios. We note the spatial concentration in the Midlands and South East reflecting the concentration of the most intensive cattle and tillage farms.

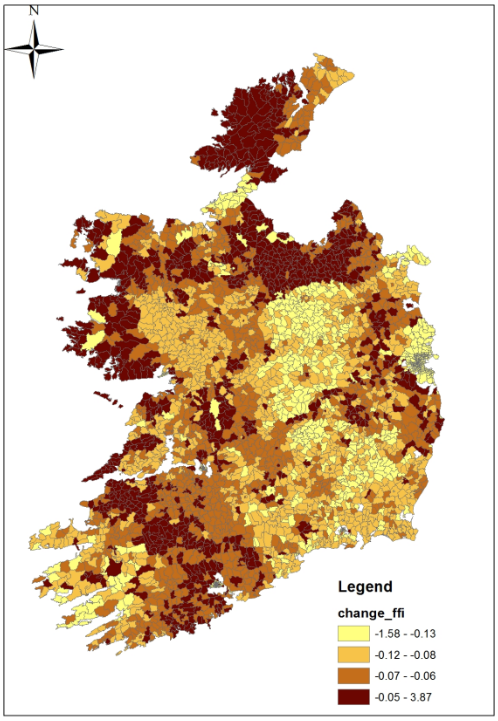
**Figure 2. Single Farm Payment per Hectare**

(a) Baseline




Source: SMILE-FARM 2010

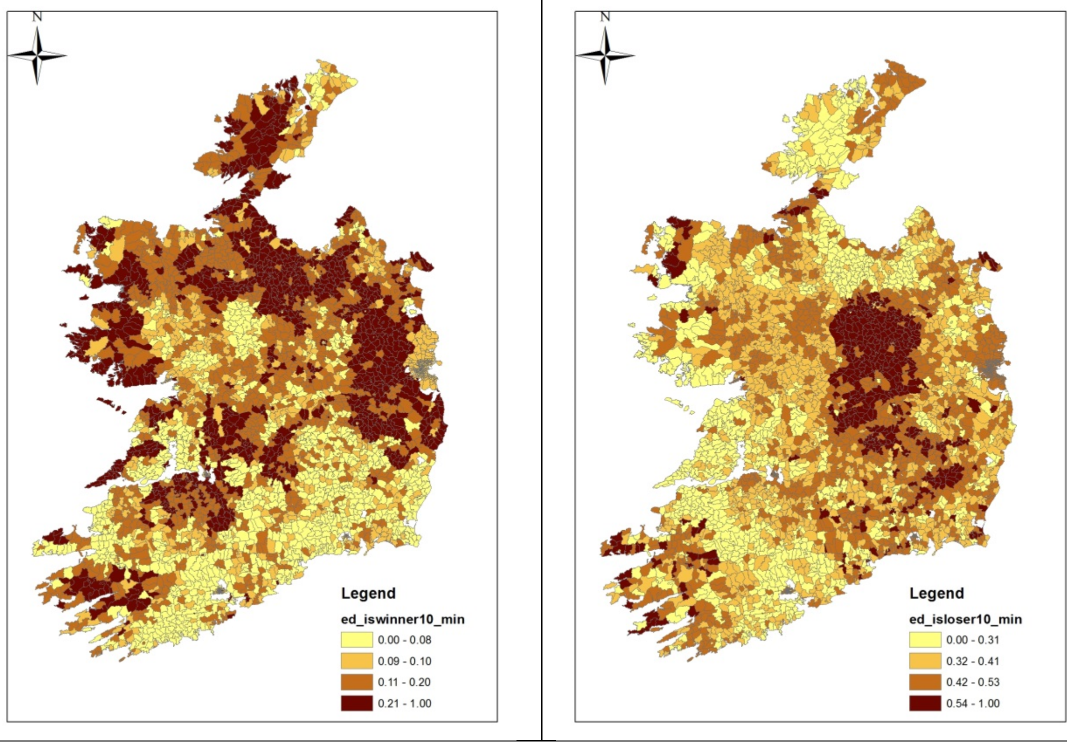
**Figure 3. Change in Family Farm Income as a result of CAP reform**




Source: SMILE-FARM 2010

**Figure 4. Share of Winners and Losers by Electoral Division**

(a) Winners (b) Losers




Source: SMILE-FARM 2010

Figure 4 reports the spatial impact of the CAP reform in terms of the change in family farm income. Most districts have a negative change as the overall payments has declined. The darkest colour on the map are the areas which lose less than 5% of income or gain and are mainly concentrated in the peripheral areas. The biggest losers are the in areas with the highest single farm payments in the midlands and in the South East.

In Figure 5, we report the spatial pattern of winner (a) and losers (b) of more than 10 % of the value of their original single farm payment. The share of winners, as one would expect, is high in the areas where family farm income increased (or least fell least) in figure 4. However there are areas such as part of the East coast where there are winners. These are however counter balanced by losers in the same area. The beef producing areas in the East combine both intensive cattle farms and less intensive cattle farms, with the former losing and the latter winning. More generally, the losers occur in the more typically intensive cattle areas of the midlands and in the cereal producing areas in the South East. Given challenges in relation to the sampling frame of the Teagasc National Farm Survey, one needs to be cautious about interpretations in relation to the changes on the peninsulas along the West coast.

In table 4 we highlight that the Gini measure of direct payments for those with non-zero payments declined from a Gini of 0.424 to 0.402, reflecting the more equal distribution of direct payments. It is consistent with the decline in Gini observed in Donnellan et al., (2013) utilising administrative data. This fall of 2.4 points is relatively substantial and is equivalent to the change in the Gini amongst household incomes during the economic crisis. However, interestingly, the impact on family farm incomes is to increase inequality. The reason is that there are some transfers from farms with high single farm payments both lower net margins to farms with low single farm payments and higher net margins and as a result the variability of family farm incomes increase.

**Table 4. Change in Inequality of Family Farm Incomes and Direct Payments due to the Reform**

| | Baseline | Reform |
|---|---|---|
| Direct Payments | 0.424 | 0.402 |
| Family Farm Income | 0.671 | 0.682 |

Source: SMILE-FARM 2010

We would also like to quantify the change in the spatial distribution of income and direct payments as a result of the reform; we would also like to understand how redistribution there is within spatial entities and between spatial entities. To do this, examining the variability of incomes between individuals within and across regions, we decompose inequality into population sub-groups, where groups are districts or other spatial entities. One can then decompose total variability of incomes into a factor attributed to between group variability across space and variability within a district (within group variability). Utilising the $I_2$ index, half the squared coefficient of variation, within group variability is defined in formula (6), between group variability is defined in formula (7).[6] Utilising the fact that the population share is $\left(\frac{1}{n}\right)$, we see that between person inequality, is in fact the inequality of mean lifetime income.

$$I_w = \sum_j w_j I_j \qquad (6)$$

[6] Björklund and Palme, 1997 use a similar decomposition method but instead use the $I_0$, Theil L and $I_1$ Theil T indices.

where $w_j = v_j^2 f_j^{-1}, v_j$ the income share of each person $j$ and $f_j$ is the population share of person, in this case $\left( 1/n \right)$.

$$I_b(y) = \frac{1}{2}\left[ \sum_j f_j \left( \frac{\mu_j}{\mu} \right)^2 - 1 \right] = \frac{1}{2}\left[ \frac{1}{n} \sum_j \left( \frac{\mu_j}{\mu} \right)^2 - 1 \right] = I(\mu) = \bar{I} \tag{7}$$

where $\mu_j$ is the mean lifetime income for person $j$ and $\mu$ the mean population lifetime income. We will utilise our simulated data in SMILE to compare the degree of between and within spatial district inequality and examine the impact that tax-benefit policy has in the level of both.

Table 5 reports the share of total inequality divided into between district and within district variation. We note in the baseline that about 85% of variation in family farm income is accounted for by within area and between farm variation. Thus the vast majority of variation occurs within district. This reflects the fact that there are large farms and small farms in the same area and farms of different systems. There may also be soil and other agronomic variation as well as variation in management characteristics. Nevertheless the between district share of variability is higher for farm income than incomes of other types such as household disposable income (See O'Donoghue et al., (2013c), reflecting the importance of environmental or agronomic variation in farm productivity and farm systems.

The net impact of the reform is that the share of spatial or between district variation of family income declines and direct payments to a greater extent. This reflects the flattening of the direct payment, with a lower reliance on spatial concentrations of particular sectors such as cattle and tillage that were historically more likely to be in receipt of farm payments.

**Table 5. Spatial Distributional Statistics pre and post reform (Share of total inequality)**

| | Between District | | Within District | |
|---|---|---|---|---|
| | Baseline | Reform | Baseline | Reform |
| Direct Payments | 17.8 | 13.9 | 82.2 | 86.1 |
| Family Farm Income | 14.5 | 13.1 | 85.5 | 86.9 |

Source: SMILE-FARM 2010

## 6. Conclusions

The objective of this paper was develop a methodology to assess spatial distributional impact of the Common Agricultural Policy Pillar 1 Reforms that will take place from 2015. In Ireland, these reforms will move from a historical based payments system in place since 2005 with a transition towards a flatter system with a combination of a basic payment and a greening related payment. There are is significant spatial pattern of different farming systems reflecting agronomic and environmental conditions, which historically had different direct payment eligibility and as a result the reforms may have a spatial impact.

The challenge in undertaking such an exercise is that there is no suitable dataset available. While the Irish Farm Accountancy Data Network Data, the Teagasc National Farm Survey contain sufficient data to measure the distributional impact of the reform, they do not have sufficient data to model the spatial distribution.

This paper uses a Quota sampling method which is a simpler but computationally more efficient measure than other methods. The paper then models the spatial distribution of farm incomes and direct payments. It captures well the pattern of farm activity on either side of the Commins-Frawley line that divides the country.

We complete the study by modelling the spatial distribution of CAP reform. Primarily the biggest share of winners are in areas with lower average single farm payments in the West, North and coastal areas. Overall the reform reduced inequality in payments but increased inequality in incomes taking some payments from farms with high direct payments but low market income and giving them to farmers with lower direct payments but higher market income. However there are some areas in the East with a higher share of winners, which is cancelled out by a higher share of losers. This reflects our result that approximately 85% of farm income and direct payment variability is accounted for within area, between farm variability. As a result with heterogeneous farms within a district there can be winners and losers within the same area. Nevertheless the share of between district variability is higher than for other types of income, reflecting spatial heterogeneity in environmental and agronomic conditions. The net impact of the reform was however to reduce spatial variability.

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