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The Local Impact of the Marine Sector in Ireland

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Abstract

Much economic policy focuses on increasing or maintaining employment at a national level. However, within the EU, the move to a single market and the increased rate of globalisation has led to a recognition that not all regions would benefit from trade liberalisation. This has led to an increased focus on sub-national policies which require local development strategies. Based on their ability to recreate a complete population distribution across numerous attributes and the need for alternative frameworks to traditional macro-level modelling, spatial microsimulation methodologies have become accepted tools in the evaluation of economic and social policy. Using a spatial microsimulation model this paper seeks to estimate the spatial distribution of marine sector workers and the contribution of their income to the local economy. The spatially references outputs on employment and income generated by the microsimulation model may be used to assess the impact of the sector on the local economy in Ireland. Policy conclusions are then drawn.

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1. Introduction

As an island nation, the ocean provides an important natural resource. Ireland's ocean resource consists of 900,000km2 of seabed (Shields et al., 2005) and 1448km of coastline (Cooper, 2009). With the increased impetus on marine spatial planning for commercial and environmental sustainability (Pomery and Douvere, 2008; Suarez de Vivero et al., 2009; O'Mahony et al., 2008), the realisation of the role the marine plays in managing environmental and climate change (Adams et al., 2004) and the acknowledgment the importance and potential of the marine resource in Ireland, Sea Change – A Marine Knowledge, Research and Innovation Strategy for Ireland 2007-2013 [5] seeks to increase the competiveness and sustainability of the sector.

Given this background and recognising that economic considerations often dominate government decisions with regard to conservation and management practices the economic valuation of the marine resource is now commonly advocated (Lal, 2003; Adams et al., 2004). Based on this realisation policymakers and practitioners within the marine sector require a fleet of economic indicators to understand, estimate, or predict which marine based industries and localities are most likely to be impacted from a change in policy. These indicators may be then used to develop new policy measures to facilitate the sustainable development of the resource and its commercial activity (Suarez de Vivero et al., 2009; Lal, 2003; Adams et al., 2004).

However, the development of such a set of indicators is a challenging research area (Morrissey et al., 2011; Kildow and McIlgorm, 2011). In Ireland, a set of national (Morrissey et al., 2011) and regional indicators (Morrissey and O'Donoghue, 2012) have recently been developed to estimate the value of the marine sector in Ireland. However, policy relevant indicators are better suited to a modelling framework which emphasises micro-level processes rather than aggregated process at the macro-level (Ballas and Clarke, 2001). A local dimension to understanding the marine sector is particularly important given the largely spatial nature of the sector which is dependent to a large extent on access to the sea or via linked clusters with maritime based businesses (Morrissey an O'Donoghue, 2012).

Historically the majority of economic modelling has taken place at the aggregate or meso-level level. For example, models built using aggregate data sets (such as the census and national level surveys) are widespread and have proved very fruitful in many areas of policy analysis (see for example Longley and Batty, 2002; Stillwell and Clarke, 2004). Nevertheless, the complex dynamics which underlie markets call for more sophisticated tools to help in the formulation and evaluation of appropriate and effective public policies. Spatial microsimulation models are designed to create data micro level at the small area level if such data is missing from available datasets. Once developed, the data from microsimulation models may be used to simulate the distributional impact of differing policies or a change in policy at the micro-level (Ballas, et al., 2006).

Whilst microsimulation has a long tradition in economics (Orcutt, 1957) early microsimulation modelling demanded years of effort by large team of researchers. This burden of making and maintaining these models discouraged many researchers from considering microsimulation methods (Anderson and Hicks, 2011). However, as the pace of development of microsimulation modelling increased in the 1990s with the convergence of computing power and increased availability of data (Anderson and Hicks, 2011), microsimulation has become commonplace in demography, public health, social insurance, traffic analysis, sociology, geography and in all aspects of public policy (Ballas, et al., 2006; Anderson and Hicks, 2011; Gilbert & Troitzsch, 2005).

This paper aims to examine the spatial distribution of marine sector employees and their income contribution to the local economy. Specifically this analysis requires a methodology that will link the marine sector data collected and collated by Morrissey (2010), the Survey of Income and Living Conditions (SILC) which contains the employment and income distribution for the entire Irish population and the geo-referenced Small Area Population Statistics for 2006. Spatial microsimulation provides the necessary methodology to accomplish this task. Such a methodology would provide an important addition to the current fleet of economic indicators developed to examine the importance of the marine sector to the Irish economy. Furthermore, such an analysis would increase the use of spatial microsimulation within environmental policy, as analysis within this area to date has tended to focus on agri-environmental policy (Hynes et al., 2009; 2011). The paper continues as follows; Section 2 provides an overview of the data used to develop the marine spatial microsimulation model. In a section 3, the spatial microsimulation methodology is outlined. Using the output from the spatial microsimulation model, Section 4 examines the employment, income and distributional impact of the marine sector at the county level. Section 5 concludes with some policy recommendations.

2. Data

To inform public policy and governance within the marine sector a variety of economic data is required to estimate the impact of the sector, particularly at the local level. In terms of estimating the national or regional level impact of the sector the location of marine businesses is sufficient (Morrissey and O'Donoghue, 2012). However, to examine the contribution of the marine sector to household welfare requires data on both the location of the businesses (where the income is generated) and the residential location of workers (where the income is spent).

In terms of considering the incidence of national output, what matters is the location of the employment, while an analysis of the contribution to household welfare requires the location of the businesses, requires the location of the residence of workers.

In order to understand the local impact of the marine sector at the local level, we require information in a number of dimensions.

- The first challenge is data in relation to the marine sector. As identified above, the economic sectors that interact with the marine natural resource are not explicitly identified in national statistics or categorised in potential other data.
- Next, we require data at the local level, which in this paper we classify as the county.
- Lastly in order to do a micro based incidence analysis, we require micro data at these levels.

There are a multitude of datasets that contain one or a number of the necessary characteristics to model the contribution of the marine sector to household welfare, all the necessary data is not contained in one dataset. However, using a data matching algorithm spatial microsimulation provides a methodology to generate such a dataset. The following sections provide an overview of the datasets required to generate a dataset containing the relevant variables for the analysis at hand.

Marine Sector Data

Given the fragmented nature of the marine sector (Colgan 2008; Kildow and McIlgorm, 2010) to estimate the value of the sector a variety of data types must be employed (Morrissey et al., 2011). These data types may be broken down into three broad categories. Type 1 data is data that is in the public domain. Such estimates are generally confined to those sectors whose connection to the sea is clear (i.e. commercial fisheries, coastal transportation). Type 2 data is data that is publicly collected but is not released into the public domain. This data is at a lower industrial or geographical classification and is therefore considered confidential. Type 3 data is data that is not available in the public domain. The sectors where there is no publicly available data are those that are generally not easily recognisable as marine based. These sectors are often indistinguishable from their land based counterparts within economic datasets. For example, one cannot difference between water based recreational activities and land based recreational activities. As such, to disaggregate the Irish national IO table to include a marine component, public data was not sufficient to estimate the full value of the Irish marine sector.

In terms of collating non-public data (Type 2 data), the Irish Central Statistics Office (CSO) provides data on turnover, intermediate consumption, gross value added, exports, and employment for each sector within the Irish economy. This data is collected across a number of censuses and surveys. The censuses and surveys used for the collation of the data on the marine sector include; the Census of Industrial Production (CIP), the Annual Services Inquiry (ASI) and the Census of Buildings and Construction (CBC). These three micro datasets provide detailed firm and enterprise level information on the economic activities for each company at the four digit NACE code. In order to assure consistency of treatment across different datasets, the industry estimates should operate within an established measurement of economic activity, such as the national income and production accounts [13]. The CIP, ASI and CBC data sets collected by the CSO form the basis for the calculation of Ireland's national income and production accounts. Access may be granted to researchers interested in examining the data, through the CSO officer of statistics facility.

With regard to marine based sectors where no data was available (Type 3 data) a survey was administrated to each company within each sector (Morrissey et al., 2011). The survey was prepared in line with the CSO surveys used to obtain data for the CIP, ASI and CBC datasets. This ensured that the necessary data to populate the marine spatial microsimulation model;, output, employment and employee income, compiled between public and non-public data was consistent. Companies that provided both land-based and marine-based goods and services were specifically asked about their commercial marine-based activity (i.e. what percentage of their turnover was derived from marine-based activity). The central year for the study was 2007. To ensure temporal consistency, public datasets that were from earlier or later years were not included in the estimates. Data collected via survey specifically asked for company accounts for the year ending the 31st of December, 2007.

With regard to spatial information, Type 1 data was only available at the regional level. In terms of the Type 2 data, the CIP and CBC contain county level data for the industrial, manufacturing and construction sector. However, the equivalent datasets for the service (ASI) and agricultural, forestry and fishing sectors do not contain data at such a disaggregated spatial scale. Both datasets only include data at the regional or national level. Finally, in terms of type 3 data or the survey data, a specific question on the address (town), county and region was included. Thus, the overall dataset collated by Morrissey, (2010) contains data at a variety of different spatial scales.

Local Level Industry Data

In order to compare the marine sector with other sectors within the economy at an individual level a dataset containing geo-referenced employer and employee industry data is required. The database collected and collated by Morrissey (2010) contains the necessary output, employment and income data for each marine sector business in Ireland at varying spatial scales (Morrissey et al., 2011). This is a firm level dataset and does not contain the residential of the actual employees within each company. To obtain the residential and location of marine based employees an exogenous micro-level dataset containing detailed employment and income data is required. This dataset must also include data on the location of an individual’s workplace. One potential dataset which contains employment by industrial sector data at a local scale is the Place of Work Census of Anonymised Records (POWCAR).

POWCAR contains data from the 2006 Census. The industry categories contained in POWCAR are at a more aggregate level then the marine industry contained in the marine company dataset. The first stage therefore involves creating a new industry variable within the marine dataset based on the POWCAR industry variable. Table 1 presents the newly created marine industry variable. The POWCAR dataset also provides small area level (electoral district, ED) data for each employee by their place of residence and their place of work. POWCAR contains both place of work and place of residence data, therefore if linked to the marine dataset outline above one would be able to examine the impact of marine sector at the place of work (output and employment) and place of residence (household welfare) to be modelled across a consistent spatial scale. Therefore overcoming the spatial referencing issues contained in the marine dataset alone.

Table 1 Industrial Sectors

Marine Sector	POWCAR Sector
Sea-fisheries	Agriculture, Forestry and Fisheries
Aquaculture	Agriculture, Forestry and Fisheries
Tourism	Commerce
Other Services	Commerce
Commerce	Commerce
Renewable Energy	Commerce

Processing	Manufacturing Industry
Oil & Gas	Manufacturing Industry
Manufacturing	Manufacturing Industry
Seaweed & Biotech	Manufacturing Industry
High Tech Services	Professional Services
Shipping	Transport

Local Level Micro Data

In order to model the local welfare incidence of employment in the marine sector micro data containing both employment and income data is required. The Small Area Population Statistics (SAPS) from the Census and the related POWCAR dataset contain the number of workers and non-workers by industry and a variety of demographic and socio-economic data, such as age, marital status and socio-economic status. However, the Irish Census and its related datasets such as SAPS and POWCAR do not contain income information. In contrast, household survey data such as the Survey of Income and Living Conditions (SILC) contain income and employment information at the individual and household level. The SILC is a nationally representative longitudinal survey that began in 2003 and replaced the Living in Ireland Survey which ended in 2001. The sampling frame used for the SILC is the Irish Register of Electors.

In 2005 the SILC dataset contained 15,885 individuals. The dataset contains a variety of demographic and socio-economic characteristics, including income, employment and household composition statistics. However, while the SILC dataset contains employee and income data at the micro level this data is only available at a coarse spatial scale – the NUTS2 regional variable (containing two regions). As such, any analysis using the SILC survey is constrained to the national level. Using a matching process algorithm to link the data in the SILC with the small area level POWCAR data and the marine dataset, a much richer dataset would be obtained that would allow an examination of the employment and welfare impact of the marine sector at the local level. One can use spatial microsimulation techniques to accomplish this.

3. Methodology

Most government policies have a geographical impact, irrespective of whether they are geographically targeted or not. Therefore, to inform current and future policy making it is necessary to have data that allows the socio-economic and spatial impact of policy decisions to be examined (Ballas et al., 2007). This paper seeks to model the spatial distribution of marine sector workers and the contribution of their income to the local economy.

In order to utilise the datasets described above to undertake our local economic incidence analysis of the marine sector, we require a data enhancement technique. To do this we employ a variety of tools utilised in the spatial microsimulation literature (See Ballas et al., 2005) within the framework of the Simulation Model of the Irish Local Economy (O'Donoghue et al. 2012).

There are a number of stages in this process as follows:

- Generate the base population of households, individuals and workers ensuring that the totals are consistent with Census totals using quota sampling (Farrell et al., 2011)
- Generate calibration totals in relation to the labour market structure by local area including the numbers of workers in marine and non-marine industrial sectors described above
- Calibrate the resultant spatial micro-data to be consistent the aggregate labour market data

Spatial Microsimulation and SMILE

In order to generate a spatially referenced marine employment and income distribution, a statistical method to link the various datasets outlined in Section 2 is required. Spatial microsimulation is a means of synthetically creating large-scale micro-datasets at different geographical scales. To date a number of techniques have been developed to produce spatial microsimulation models (Ballas et al., 2005; Farrell et al., 2011). The principle methods are sampling methods such as Iterative Proportional Fitting (IPF) and various combinatorial optimisation (CO) methodologies such as Simulated Annealing (SA) or reweighting methods (Morrissey et al., 2008). However, when deciding on which procedure to employ for the analysis at hand, two main factors were important. The algorithm must be able to process a combination of individual and household constraints and have adequate run-time efficiency.

SMILE (Simulation Model of the Irish Local Economy) is a static spatial microsimulation model (Morrissey et al., 2008). SMILE 2002, based on the 2002 SAPS and the Living in Ireland Survey (2001) used a simulated annealing algorithm to examine a host of policy specific areas including health service demand and supply (Morrissey al., 2008; 2010), labour force participation (Morrissey and O'Donoghue, 2011) and agri-environmental policy (Hynes et al., 2009) at the small area, electoral district (ED) level. However, whilst simulated annealing allows one to model both individual and household processes, the algorithm requires significant computational intensity due to the degree to which new household combinations are tested for an improvement in fit during simulation (Farrell et al., 2011). As a result, using the SAPS (2006), SILC (2005) and POWCAR (2006) datasets a relatively simple method known as quota sampling was developed by Farrell et al., (2011) for SMILE 2006. This process will be outline below; however for an in-depth outline of the process please see Farrell et al., (2012).

Quota Sampling (QS)

The QS methodology is based on a probabilistic reweighting. Similar to the process of SA (Morrissey et al, 2008), survey data are reweighted according to key constraining totals, or 'quotas', for each local area. In the population version of SMILE, the unit of analysis consists of individuals grouped into households while the constraints can be either at the individual or household level. One of the key goals of the QS method is to achieve computational efficiency. To achieve this efficiency the QS process is apportioned into a number of iterations based on an ordered repeated sampling procedure (Farrell et al., 2011). The final step in the sampling procedure allows the constraining criteria to be broadened to ensure the marginal totals of the matching census tables are met with improved accuracy and computational efficiency.

A process of random sorting to ensure the suitability of a household given concurrent quota counts is fundamental to the efficiency gains of the QS method. The basic selection process operates as follows. Households which comply with concurrent quota counts are extracted from the microdata population. These observations are sorted randomly and assessed in order of convenience. A household is selected as a resident of a district if their demographic profile the constraining totals for an ED. To improve efficiency, this procedure considers both individual and multiple households in one simulation iteration. As stated, the candidate sample at each stage is limited to households eligible according to the quota counts at the initiation of the procedure. If a number of households are chosen such that the total population assigned is less than or equal to the smallest constraining quota the maximum number of households is assigned in one iteration. This ensures that quota counts are not exceeded, regardless of the distribution of characteristics. Thus, if the preliminary selection complies with concurrent quotas, it is admitted to the small area sample. Quota counts indicating how many more individuals of each constraining quota criterion are then amended, reduced by the sum of the characteristics of the assigned household(s). For individual level constraints, the running totals per constraint are incremented by the number of people in the household with that particular constraint. For household level constraints, it is incremented by 1. This process is repeated until all the small area defined quotas are reached.

Calibration

The computation cost of quota sampling and other methods of generating small area data limits the number of constraints (Morrissey and O'Donoghue, 2011). However the spatial heterogeneity of the simulated data depends upon the holistic nature of the constraints. The need to optimise computational efficiency, whilst ensuring the spatial heterogeneity of the simulated dataset means that a calibration mechanism must be used (Morrissey and O'Donoghue, 2011). The purpose of the calibration procedure is to align disaggregated data within SMILE with exogenous spatial distributions of income (Morrissey and O'Donoghue, 2011). The procedure presented here operates in two stages. The first stage estimates a set of equations (logistic or multinomial) determining the presence of an income based on labour force participation. The second step involves predicting the level of income for individual using logged income regression models. A full description of the calibration method is provided by Morrissey and O'Donoghue, (2011).

Using a probabilistic alignment technique the spatial distribution of unconstrained labour market characteristics are calibrated against Small Area Population Statistic (SAPS) totals. Once the correct distribution of these variables has been established, the level of income is calibrated according to external county level national accounts. Definitional differences between micro level and national accounts data prohibit calibrating income in absolute terms, as scaling average income by source to the national accounts total can affect the distributional properties of the data. Thus, the calibration procedure is augmented in a step-wise fashion to ensure average county income by income source (i.e. market income, social welfare income, capital income, etc) corresponds to county level national accounts. This allows the same distribution properties of the underlying income data to be largely maintained.

SMILE Marine

The SMILE model thus far contains a fully calibrated residential distribution of employees and their income by industry for 2006. However, in order to model the local impact of the marine sector, the employment location of workers in the sector is required. To find both the residential and employment location of workers the marine dataset must be linked to the SMILE population dataset. Although it is impossible to identify specific business in the SMILE model (via the linked POWSAR dataset), one may assume that the residential distribution of each employee within a wider industrial classification is the same for the relevant marine sub-sector (Table 1). Sampling the number of workers from the marine sub-sector, as outlined above, the residential distribution of these marine employees may be obtained. The next section presents the employment contribution and income contribution of the marine sector relative to the non-marine sector at the county level. For the purpose of this paper county refers to administrative boundary of which there are 34 in Ireland. Such an analysis at this level of spatial scale would not be possible without the techniques offered by spatial microsimulation.

4. Results

Marine Employment Contribution

Table 2 reports the county employment rate, the percentage of marine employment by county and total marine employment as a percentage of total county employment and the coastal status of the county. From Table 2, it can be seen that although the marine sector is relatively small sector nationally (it represented 1% of GVA in 2007), it is of relatively strong importance in counties of the North and West (Mayo, Donegal, Kerry and Galway) of Ireland. This is a function of both the coastal location of these counties and their relative peripherality and employment profile of these counties relative to the East Coast (Morrissey et al, 2011). Although much of the marine sector is in the non-traditional marine sectors, particularly the marine service sector (Morrissey et al., 2011) and thus not necessarily tied to the coastline the vast majority of employment is within coastal counties – building upon the scale, knowledge spillover and agglomeration effects of existing marine businesses (Morrissey and O'Donoghue, 2012). From Table 2 one can see that the majority of marine sector employment occurs in the counties with a high absolute employment share in the sector. Cork however is the main exception, having a mid-ranked employment share from marine activities but having the highest proportion of total marine employment due to its larger size.

Table 2 Share of Marine Employment per County (Source: SMILE Marine)

County	Region	County Employment Rate	Overall % of Marine Employment by	County % of Employment by Marine Sector	Coast

			County		
Donegal	Border	47.8	12.6	3.6	1
Sligo	Border	51.7	2.5	1.5	1
Louth	Border	54	2	0.7	1
Leitrim	Border	50.2	0.3	0.4	Minor
Cavan	Border	52.4	0.3	0.2	0
Monaghan	Border	53.2	0.2	0.2	0
South Dublin	Dublin	57.5	3.1	0.5	0
Fingal	Dublin	64	3.1	0.4	1
Dublin City	Dublin	56.5	6.3	0.4	1
Dun Laoighaire	Dublin	52.6	1.9	0.4	1
Wicklow	East	53.5	2.4	0.7	1
Kildare	East	61.8	1.3	0.2	0
Meath	East	60.3	1	0.2	0
Longford	Midlands	50.4	1.2	1.4	0
Westmeath	Midlands	54.8	0.4	0.2	0
Laois	Midlands	54.8	0.2	0.1	0
Offaly	Midlands	53.7	0.2	0.1	0
Clare	Mid-West	54.3	4	1.3	1
Limerick	Mid-West	52.2	1.1	0.2	0
Tipperary NR	Mid-West	52.1	0.1	0.1	0
Wexford	South East	52.1	5.4	1.6	1
Waterford	South East	51.9	3.5	1.2	1
Tipperary SR	South East	51	0.7	0.3	0
Carlow	South East	53.1	0.2	0.2	0
Kilkenny	South East	54.1	0.3	0.1	0
Kerry	South West	50.5	7.5	2	1
Cork	South West	53.7	17.4	1.3	1

Mayo	West	48.8	9.3	2.9	1
Galway	West	52.7	10.9	1.7	1
Roscommon	West	49.9	0.5	0.3	0
Total			100		

NB. Some counties such as Leitrim, South Dublin and Meath are predominantly inland counties with very small coastlines and thus are deemed as non-coastal.

Income Contribution

Table 3 presents the average marine and non-marine sector contribution to employment income by county. From Table 3, it can be seen that the average marine sector income contribution (€34,034) is higher than the non-marine contribution (€30,153) in coastal counties. Table 3 also provides the marine versus non-marine sector income ratio by county. In total it can be seen that the marine sectors have a positive income premium of on average 12% compared to non-marine sectors. Although the counties with the highest marine based employment rates (Donegal, Mayo, Kerry and Galway) experience a slightly higher than average premium of between 10 and 15%, the highest premiums occur in non-coastal counties such as Offaly, Cavan and Tipperary North Riding. This is due to the low level of marine employment in non-coastal counties (0.69% compared to 6.39% in coastal counties) relative to average marine sector income as a whole. This is a further indication of the income premium in the marine sector.

Table 3 Average Employment Income for Marine and non-Marine Sectors (Source: SMILE Marine)

County	Average Non-Marine Income per County	Average Marine Income per County	Ratio- Marine/ Non Marine	Coast
Cavan	28446	35188	1.24	0
Donegal	25611	28090	1.10	1
Leitrim	27265	23086	0.85	Minor
Louth	32434	34696	1.07	1
Monaghan	28203	39144	1.39	0
Sligo	28787	33771	1.17	1
Laois	27663	25687	0.93	0
Longford	28759	31916	1.11	0
Offaly	28016	47078	1.68	0
Westmeath	28458	32677	1.15	0
Galway	28906	32860	1.14	1

Mayo	28240	32167	1.14	1
Roscommon	28393	30095	1.06	0
Kildare	32176	35505	1.10	0
Meath	30178	27315	0.91	0
Wicklow	33591	36349	1.08	1
Clare	29208	34649	1.19	1
Limerick	31376	36382	1.16	1
Tipperary NR	30347	50862	1.68	0
Carlow	25701	27783	1.08	0
Kilkenny	27613	31298	1.13	0
Tipperary SR	30187	29407	0.97	0
Waterford	30608	34845	1.14	1
Wexford	28405	32346	1.14	1
Cork	31144	33901	1.09	1
Kerry	27537	31441	1.14	1
Dublin City	35740	37536	1.05	1
South Dublin	35959	37049	1.03	0
Fingal	38124	39504	1.04	1
Dun Laoighaire	37521	38814	1.03	1
County Average	€30,153	€34,034		

Examining the composition of marine income by sub-sector indicates that average income across the sector is driven by sub-sector. Table 4 reports the ratio of average income by marine sub-sector relative to the national average. It can be seen from Table 4 that the shipping sector has earnings below the national average, whilst in contrast commerce (1.28) and renewable energy sectors (1.14) have income averages significantly above the national average. However, both these sectors are non-traditional marine sectors (Morrissey et al., 2010). The renewable energy sector is a high tech, research and development based sector, whilst the marine commerce sector comprises marine based financial services and insurance, with the majority of these companies located in urban coastal locations. The characteristics of these sectors within the wider Irish economy would indicate that employees would earn higher than average incomes. However, what is of interest is that traditional marine sectors such as fisheries (1.05) and aquaculture (1.01), which are predominately located in peripheral, coastal areas have a slightly higher than average income.

Mean income however only tells part of the story of the impact of a sector on the local economy. The spread of incomes is also important. A higher average with a lower spread indicates that the majority of individuals who work in the sector have earnings above average. The spread of income may be measured using the I2 inequality statistics, which may be defined as:

$$I_2 = \frac{1}{2}\left(\frac{\sigma^2}{\mu^2}\right) \qquad (1)$$

where σ^2 is the standard deviation of income an $\mu 2$ represents average income.

Table 4 Sub-Sectoral Average Earnings (State = 1)

Sector	Ratio Average Earnings relative to National Average
Non Marine Income	1.000
Marine Sub-Sectors	
Shipping	0.935
Tourism	1.107
Other Services	1.143
Sea-fisheries	1.047
Aquaculture	1.012
Processing	1.001
Oil & Gas	1.032
Manufacturing	1.058
Commerce	1.278
Seaweed	0.981
Renewable Energy	1.142

Of the 26 counties with a higher average marine income compared to non-marine, 16 have a lower spread than the non-marine sectors. This confirms that individuals who work in the marine sector in these counties have higher than average earnings and are grouped more closely together than other sectors. Ignoring Monaghan and Limerick, which have very few marine sector workers, the spread of earnings rises with the marine employment rate. The anomaly created by Monaghan and Limerick may be due to counties with relatively small sectors having lower spreads due to fewer workers. Another reason may be that these counties display specialisation in specific high income marine sectors. Table 6 examines this hypothesis further and provides the marine sub-sector share of employment by county. From Table 6 it can be seen that there is no obvious concentration of sub-sectoral activity in counties with smaller sectors. In these counties, there tends to be smaller concentrations of multiple sectors, rather than sectors building any specific concentration. As such, the strong income spread displayed in counties with small marine sectors, such as Monaghan and Limerick is due to fewer marine workers in these counties.

Table 5 Earnings Inequality per County (Source: SMILE-Marine)

	Non-Marine	Marine	Ratio
Cavan	0.87	0.55	0.63
Donegal	0.75	1.03	1.38
Leitrim	0.87	0.27	0.31
Louth	0.78	1.11	1.41
Monaghan	0.69	2.25	3.27
Sligo	0.76	0.41	0.53
Laois	0.74	0.47	0.63
Longford	0.97	0.81	0.84
Offaly	0.78	0.88	1.13
Westmeath	0.79	0.54	0.69
Galway	0.77	0.80	1.04
Mayo	0.85	1.27	1.50
Roscommon	0.88	0.44	0.51
Kildare	0.71	0.34	0.48
Meath	0.76	0.28	0.37
Wicklow	0.75	0.44	0.58
Clare	0.80	1.07	1.34
Limerick	0.72	2.10	2.91
Tipperary NR	0.80	0.29	0.35
Carlow	0.74	0.67	0.90
Kilkenny	0.85	0.21	0.25
Tipperary SR	0.75	0.50	0.67
Waterford	0.84	1.02	1.22
Wexford	0.82	0.62	0.75
Cork	0.74	0.83	1.12
Kerry	0.84	0.70	0.83
Dublin City	0.63	0.54	0.85

South Dublin	0.74	0.44	0.59
Fingal	0.71	0.49	0.69
Dun Laoighaire	0.84	0.44	0.52

Table 6 Percentage of Marine Employment by Sub-Sector (Source: SMILE-Marine)

Marine Sectors	1	2	3	4	5	6	7	8	9	10	11	12
Cavan	6	8	40	15	10	2	2	15	0	2	0	0
Donegal	9	21	1	19	10	30	0	8	0	0	2	0
Leitrim	0	18	16	12	2	6	4	37	2	0	4	0
Louth	18	21	4	16	17	19	0	2	0	0	0	4
Monaghan	8	0	43	0	8	10	3	30	0	0	0	0
Sligo	0	67	3	4	8	1	7	3	0	0	8	0
Laois	24	14	41	0	0	3	0	3	3	0	0	14
Longford	1	1	4	1	0	1	1	92	1	0	0	0
Offaly	4	19	15	12	42	0	0	8	0	0	0	0
Westmeath	6	13	18	10	6	0	1	37	6	1	0	0
Galway	2	37	1	9	12	8	1	22	6	0	1	0
Mayo	0	16	1	5	8	13	46	9	1	0	1	0
Roscommon	2	11	11	6	9	12	12	28	7	0	1	0
Kildare	24	24	15	3	5	7	0	7	4	4	0	6
Meath	21	23	14	7	0	17	0	6	9	1	1	1
Wicklow	33	45	4	6	1	3	0	6	1	0	0	0
Clare	9	72	2	4	5	3	0	2	4	0	1	0
Limerick	40	18	10	5	1	11	2	8	2	0	3	1
Tipperary NR	18	35	6	0	0	12	0	29	0	0	0	0
Carlow	10	18	28	3	13	5	0	13	8	0	3	3
Kilkenny	32	42	0	4	0	4	0	12	4	0	2	0
Tipperary SR	4	9	9	7	7	5	1	58	0	0	0	0
Waterford	24	42	1	18	7	3	0	3	2	0	0	0
Wexford	13	48	2	20	3	9	0	2	2	0	1	0
Cork	14	31	4	13	7	17	1	9	1	0	1	1
Kerry	0	60	2	12	7	14	0	2	0	0	3	0

Dublin City	36	33	5	5	0	5	0	8	5	2	0	1
South Dublin	31	38	5	3	0	5	0	9	3	3	2	2
Fingal	33	35	4	4	0	6	0	10	3	4	0	2
Dun Laoighaire	46	33	2	5	0	4	0	5	2	1	0	1

Note - Marine Sector: 1 - Sea-fisheries; 2 - Aqua-culture; 3 - Processing; 4 - Oil & Gas; 5 - Manufacturing; 6 - Seaweed & Biotech; 7 - Tourism; 8 - Other Services; 9 - Commerce; 10 - Renewable Energy; 11 - Shipping; 12 - High Tech Services

The analysis provided above allows one to examine both the employment and income impact of the marine sector at the county level in Ireland. Whilst Morrissey et al., (2011) and Morrissey and O'Donoghue (2012) provided a national and regional analysis of the marine output and employment, respectively, due to the varying spatial data contained in the marine dataset, a lower level county analysis was not achievable. Furthermore, as the marine dataset collected by Morrissey (2010) did not contain residential information for each employee, a welfare analysis based on income was also not possible. Thus, it was only through the use of spatial microsimulation techniques that a county level, employee and income analysis of the marine sector was viable.

5. Discussion

The current research interest in the spatial economic impact of the marine sector is based on the increased acknowledgement of the importance of sub-national policy in providing a foundation for national economic growth [26], the marine sectors role in developing peripheral areas [37], the sectors increasing role in high tech sectors such as biotechnology and computing (Morrissey et al., 2011) and the recognition that the development of the marine resource requires a coherent set of indicators at the sub-national level [5]. Using a spatial microsimulation model this paper developed the research theme further by examining the impact of marine employment and income at the county level in Ireland. Constrained by the spatial referencing of national datasets, previous spatial analysis on the marine sector had been limited to national and regional level.

Using the data created by SMILE it was found that although the marine sector is a relatively small sector in terms of employment nationally, it is of relatively strong importance in counties of the North and West (Mayo, Donegal, Kerry and Galway) of Ireland. In terms of the welfare impact of the marine sector, it was found that average marine sector income contribution (€34,034) is higher than the non-marine contribution (€30,153) in 2007 and that the marine sectors have a positive income premium of on average 12% compared to non-marine sectors at the county level. Further analysis of marine income determinants at the individual level indicates that average income across the sector is driven by sub-sector. It was found that the shipping sector has earnings below the national average, whilst in contrast commerce and renewable energy sectors have income averages significantly above the national average. However, the renewable energy sector is a high tech, research and development based sector, whilst the marine commerce sector comprises marine based financial services and insurance, with the majority of these companies located in urban coastal locations. The characteristics of these sectors within the wider Irish economy would indicate that employees would earn higher than average incomes.

However, what is of interest is that traditional marine sectors such as fisheries and aquaculture, which are predominately located in peripheral, coastal areas have a slightly higher than average income. Examining the spread of income, of the 26 counties with a higher average marine income compared to non-marine, 16 have a lower spread than the non-marine sectors. This confirms that individuals who work in the marine sector in these counties have higher than average earnings.

Historically the majority of economic modelling has taken place at the aggregate or meso-level level. The complex dynamics which underlie the marine sector calls for more sophisticated tools to help in the formulation and evaluation of appropriate and effective public policies. In order to formulate such policies, it is necessary not only to understand the nature and the operation of differing policies at a macro level but also to evaluate the likely impact of these policies on activity at the local level (Morrissey and O'Donoghue, 2012). Using a micro-level methodology, spatial microsimulation, the analysis provided in this paper allows provides policymakers with a set of indicators of the importance of the marine sector at the county level in Ireland that may be used to develop future sustainable policies across the marine resource as a whole and across various marine sub-sectors.

References

Ballas, D., Rossiter, D., Thomas, B., Clarke, G. and Dorling, D. (2005). Geography matters: Simulating the local impacts of national social policies, Joseph Rowntree Foundation contemporary research issues, Joseph Rowntree Foundation, York, ISBN 1 85935 265 0 (paperback), 140 pages.

Cooper J. Coastal economies and people. Marine Climate Change Ecosystem Linkages Report Card; 2009.

Hynes, S., Morrissey, K., O'Donoghue, C. and Clarke, G. (2009). "Building a Static Farm Level Spatial Microsimulation Model for Rural Development and Agricultural Policy Analysis in Ireland." International Journal of Agricultural Resources, Governance, and Ecology, 8(2), 282 – 299.

Kildow, J.T., McIlgorm, A. (2010). The Importance of Estimating the contribution of the Oceans to National Economies, Marine Policy, 34, 367-374.

Morrissey, K., Clarke, G., Ballas, D., Hynes, S. and O'Donoghue, C. (2008). Analysing Access to GP Services in Rural Ireland using micro-level Analysis, *Area*, 40(3), 354-364.

Morrissey, K. and O'Donoghue, C. (2011). The Spatial Distribution of Labour Force Participation and Market Earning at the Sub-national level in Ireland, *Review of Economic Analysis*, 3(1).

Morrissey, K., and O'Donoghue, C. (2012) Marine Economy and Regional Development, Marine Policy 36 358–364.

Sea Change (2007). Sea Change: A Marine Knowledge, Research and Innovation Strategy for Ireland 2007-2013, Marine Institute, Renvyle, Galway.

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