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Spatial Microsimulation for Regional Analysis of Marine Related Employment

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1. INTRODUCTION

There are a wide range of methodological frameworks and techniques for policy evaluation and socio-economic impact assessment. These include input-output approaches, social accounting matrix–Leontief models, computable general and partial equilibrium modelling techniques and micro-simulation models. It has been noted that many of these approaches and methodologies have had a long successful history in socio-economic impact assessment (Ballas, 2005; Ballas et al. 2012; O’Donoghue, 2014). However, the absence of detailed data on marine industry markets calls for more sophisticated tools to help in the formulation and evaluation of appropriate and effective marine policies. In order to evaluate such policies, it is necessary not only to understand the nature and the operation of the marine sector at a macro level but also to evaluate the likely impact of these policies on marine activity at the local level. Indeed, Morrissey (2017, p125) argues that “policy analysis in the marine sector is better suited to a modelling framework, which emphasizes the heterogeneity of the sector at the micro-level rather than aggregated macro-level processes”.

Currently, many coastal countries measure the size of their ocean economies viewing it as a necessary requirement for effective marine policy formation (Colgan, 2013; Zhao et al., 2014; To and Lee, 2018; Stebbings et al., 2020). Attempts have also been made to build a unified ocean economy classification system (Park & Kildow, 2014; OECD, 2016; European Commission, 2021). Ireland, which is the geographical focus of this paper, has also had statistics compiled on its ocean economy on a regular basis since 2005 (SEMUR, 2019). Due to the increasing awareness of the contribution of the marine environment to the Irish economy and to societal welfare, both local and national political bodies have an interest in identifying the spatial distribution of the ocean economy. With that in mind and in line with the EU Maritime Spatial Planning Directive, the Irish Government have developed a National Marine Planning Framework (NMPF) (DHPLG, 2021). Such marine spatial planning requires accurate, extensive data collection and management of both environmental and socio-economic data that facilitates policy impact assessment at a scale that is below the national level (Schaefer & Barale, 2011).

There is therefore a need to understand, estimate or predict which type of marine enterprise and geographical areas are mostly affected from a specific marine policy or a change in general public policy. As pointed out elsewhere in this special issue (O’Donoghue et al., 2021) and by others (Morrissey, 2017), this type of local level analysis for marine economic impact assessment can be addressed in a spatial microsimulation framework. Using spatial data generated for marine enterprises and the availability of employment figures at a small area population level it is possible to generate a spatial microsimulation model that allows for ocean economy policy analysis at a finer spatial scale rather than is commonly the case (Foley et al., 2014).

This paper demonstrates how such a modelling framework can be generated. It first reviews the use of the spatial microsimulation method for public policy analysis. The data sets used in the analysis are then presented in section 3. Section 4 describes the approach taken to generate the marine employment observations in the previously developed Simulation Model of the Irish Local Economy (SMILE). The section also provides a brief outline of how the original SMILE model itself is created (O'Donoghue, 2014). The results of the spatial microsimulation model are shown in section 5 and a policy simulation is carried out to investigate the spatial impact of the Covid-19 pandemic on marine industry employment. Finally, section 6 offers some conclusions and recommendation for future model developments.

2. SPATIAL MICROSIMULATION MODELLING

Micro-datasets are primarily either official census publications or individual/household survey data. In general census data includes a variety of socio-economic variables, such as age, marital status and education level and a geographical component. However, variables such as income level, personal pension information, health status, and information on marine related activity are not included due to data confidentiality. As such, using the census of population for explanatory research is restricted due to data limitations. In contrast, individual/household survey based datasets often contain more income-related and socio-related variables. However, due to the cost and administrative difficulties in collecting such data, surveys are usually small in scale and can be misrepresentative of the general population. A solution to these limitations and data unavailability was first provided by Orcutt in the 1960s. This solution was a microsimulation modelling approach. Orcutt et al. (1961) proposed building large-scale; attribute rich datasets from simulated data, using reweighting algorithms that would combine the strengths of survey and census based datasets.

Spatial microsimulation adds a geographical dimension to the microsimulation modelling approach and is designed to analyse the relationships among regions and localities and to project the spatial implications of economic development and policy changes across regions (Ballas et al., 2006; Tanton et al., 2014). The first geographical application of microsimulation was developed by Hägerstrand (1967) who employed micro-analytical techniques for the study of spatial diffusion of innovation. Later Wilson and Pownall (1976) addressed the aggregation difficulties that were associated with traditional comprehensive spatial models of urban systems at that time.

Since these early developments in the field of spatial microsimulation there has been an explosion of interest in the use of the technique for regional and rural policy analysis. National level spatial microsimulation models are now available across many countries and are used to examine the regional impacts of changes in public policy. The SYNAGI (Synthetic Australian Geo-demographic Information) model in Australia (Harding et al., 2006), SimAlba in Scotland (Campbell and Ballas, 2016) and the SESIM model in Sweden (Larsson et al, 2019) are just some examples used to examine a broad range of issues from the analysis of the aging population, to health care, housing, pension reform, tax and cash transfer

policies and retirement incomes. Of particular interest to the analysis here is a spatial microsimulation model that have been developed in Ireland. That model is the Simulation Model of the Irish Local Economy (SMILE), developed by Teagasc, the National University of Ireland Galway and the University of Leeds, to assess the regional impacts of public policy changes in Ireland (Farrell et al., 2013). The model is adapted in this paper to analyse the spatial change in marine enterprise employment in Ireland following a significant shock to the sector.

Morrissey et al. (2014) also employed the SMILE model in a marine policy context to examine the employment and income contribution of the marine sector at the county, small area and household level. Using a probabilistic alignment technique the authors calibrated the spatial distribution of marine employees against known county level totals. In the calibration it was assumed that the residential distribution of employees within a marine industry was the same as the wider industrial classification to which it belonged. This wider industrial classification was available for each individual in the SMILE simulated population. This research builds on the work of Morrissey et al. (2014) with more up to date marine employment data and provides more spatial accuracy in terms of the marine industry matching process by calibrating not just to county level marine industry employment totals but also to marine enterprise data available at a more refined spatial scale, the Electoral Districts (ED) level. This matching process is described in more detail in the methodology section.

Spatial microsimulation has four main advantages: first, it allows data from various sources to be linked if datasets contain at least one attribute in common (for example the Living in Ireland Survey dataset and the Census of Population dataset which have a number of overlapping socio-demographic variables). Secondly, the models are flexible in terms of spatial scale; that is data can be re-aggregated or disaggregated. For example, the marine industry level spatial microsimulation outputs can be aggregated to counties (by ED), regions (by province) or the country as a whole. Third, spatial microsimulation models store data efficiently as lists. Finally, the models allow for updating and projecting.

On the other hand, one of the biggest drawbacks of spatial microsimulation frameworks is the difficulty in validating the model outputs. As Tanton and Edwards (2013) point out, given that one of the objectives of creating synthetic microdata is to create data that does not currently exist or to estimate distributions of variables which were previously unknown for small geographic areas, validation of the results is difficult. Moreover, spatial models can require a large amount of computational power, and require high storage capacity machines to run.

Ballas et al. (2005) argued that the spatial microsimulation method typically involves four major procedures:

The construction of a microdata set (when this is not available)

Monte Carlo sampling from this data-set to ‘create’ a micro-level population **with spatially disaggregated location information for each observation**

What-if simulations, in which **the spatial distribution of the impacts** of alternative policy scenarios on the population are estimated

Dynamic modelling to update the basic microdata set

By permitting analysis at the individual level, microsimulation methods allow one to assess variations in the distributional effects of different policies (Callan, 1991; Ballas et al., 2006; Hancock and Sutherland, 1992; Tanton et al. 2014). In addition, microsimulation modelling frameworks provide the possibility of defining the goals of economic and social policy, the instruments employed and also the structural changes of those affected by socio-economic policy measures (Gupta and Kapur, 2000). Spatial microsimulation therefore allows for a regional or local approach to policy analysis. In the current application it does so by simulating the regional variation in marine industry employment and by analysing the regional impact on that employment due to the introduction of a new public policy – the Irish Government’s Covid-19 pandemic unemployment benefit scheme.

3. THE DATA

In order to examine the spatial distribution of marine industry employment, this paper makes use of an existing spatial microsimulation model for the general Irish population; the aforementioned SMILE (Spatial Microsimulation Model of the Irish Local Economy) model. SMILE is a static spatial microsimulation model designed to simulate regional welfare, income, and labour distributions in Ireland and thus provide a basis for regional economic and public policy analysis (Farrell et al., 2013). Linking the marine enterprise data and the aggregate employment statistics from the ocean economy report allows for the analysis of regional employment effects from policy changes and/or shocks at different spatial scales. How the SMILE model is created and the additional marine linkages preformed is described in the methodology section that follows. Firstly however the data sets used in the marine linkage are introduced. In order to examine the impact of a public policy change on the regional distribution of marine related employment the SMILE model has to be linked to marine enterprise location data and marine employment aggregate statistics.

Multiple data sources are used to create the ocean economy workforce in the spatial microsimulation model. In particular ocean economy national level employment data had to be linked with location specific marine enterprise data which in turn had to be mapped to the existing synthetic individuals in the SMILE model. The national level ocean economy employment data was sourced from the Socio-Economic Marine Research Unit (SEMRU) Irish ocean economy reports (SEMRU, 2019). This data in turn is based on industry

classifications grouped by their NACE code¹, a European classification system which groups organisations by their business activities and assigns a 2, 3, or 4-digit code to each industry. For some of the smaller industries SERMU also carries out its own business surveys.

Table 1. Estimated direct turnover, GVA and employment by industry, 2019 (€m)

Industry	Turnover (€m)	GVA (€m)	Employment (FTEs)
Shipping and Maritime Transport	2,237	601	4,908
Marine Tourism and Leisure	1,213	610	17,471
International Cruise Industry	57	22	...
Marine Retail Services	172	77	954
Sea Fisheries	270	134	2,390
Marine Aquaculture	172	98	1,948
Seafood Processing	652	127	2,408
Oil and Gas Exploration and Production	396	52	150
Marine Manufacturing, Construction and Engineering	141	70	860
Advanced Marine Technology Products and Services	100	43	706
Marine Commerce	236	70	402
Marine Biotechnology and Bio-products	79	31	563
Marine Renewable Energy	59	38	482
Total	5,786	1,973	30,852

¹ Eurostat ISSN 1977-0375 – NACE Rev.2. As outlined in SEMRU (2019) many of the ocean economy industries are a combination of a number of relevant NACE codes.

Source: See SEMRU (2019) for full breakdown on methodology used and data sources.

Table 1 presents the latest estimates from SEMRU on the Irish ocean economy in 2019. In particular it shows the estimated value of direct turnover, gross value added (GVA) and employment across 12 marine related industries. The spatial microsimulation modelling approach is solely concerned with enterprises that originate in or have headquarters in Ireland. The international cruise ship industry is therefore excluded. In that instance the international cruise ship parent companies are not stationed in Ireland and come with their own foreign based crews. Hence no Irish ocean economy employment figures are shown for the industry in table 1. Additionally, the focus here is on private marine enterprise workers. Therefore, those individuals employed in public sector bodies such as government agencies, the defence forces or third level institutions, and involved in marine related issues, are not included in the analysis.

Table 2. Irish ocean economy industries represented in the marine business directory

Marine Sector	Count of Businesses	% of Total in Ocean Economy
Marine Tourism and Leisure	934	32.01%
Marine Aquaculture	366	12.54%
Shipping and Maritime Transport	264	9.05%
Marine Retail Services	238	8.16%
Seafood Processing	206	7.06%
Marine Manufacturing, Construction, and Engineering	191	6.55%
Sea Fisheries	189	6.48%
Oil and Gas Exploration and Production	186	6.37%
Marine Advanced Technology, Products, and Services	133	4.56%

Marine Bio-Technology and Bio-Products	90	3.08%
Marine Renewable Energy	79	2.71%
Maritime Commerce	42	1.44%
Grand Total	2918	100%

The second key data source used in the analysis is the Marine Institute/SEMRU Business Directory. This is a directory of all marine related businesses for the year 2019. Upon completion of the marine business directory, it contained 2,918 businesses that related to the Irish ocean economy. It represented 12 of the 13 Irish ocean economy industries, shown in Table 1 (again cruise related businesses were excluded from the directory). Table 2 shows the number of enterprises represented by each industry in the ocean economy and each industry's share of total enterprises in the ocean economy. As can be seen, a large proportion of the businesses are in the marine tourism and leisure category (32.01%). This sector included water sports, seaside recreation, and non-professional angling. The high share of marine tourism and leisure enterprises in total ocean economy enterprises is unsurprising given over 50% of all employment in the Irish ocean economy is also in this industry. The dominance of the tourism sector in total ocean economy employment is a common feature of ocean economies globally (European Commission, 2021).

Figure 2 displays the density and spatial distribution of the marine enterprises across the country. Using Hynes and Farrelly (2012)'s definitions of Irish statistical coastal regions, defined at a number of alternative spatial tiers (based on electoral districts (EDs), county boundaries and EU NUTS 3 regions²), it was found that nearly 75% of the marine enterprises are located in a shoreline ED, 95% of the marine enterprises lie with a coastal county, and coastal NUTS3 regions contain just under 98% of all marine enterprises³. Industries such as

² The Nomenclature of Territorial Units for Statistics (NUTS) was established by Eurostat more than 30 years ago in order to provide a single uniform breakdown of territorial units for the production of regional statistics for the European Union.

³ Shoreline Electoral Districts: establishments located in an electoral district (ED) that is immediately adjacent to an ocean or sea, included estuaries and bays. Of the 3400 EDs in the country, 628 are Shoreline Electoral Districts. Coastal County: establishments located in a county that has a shoreline of any length adjacent to an ocean or sea, included estuaries and bays. 15 of the 26 counties in the Republic of Ireland are Coastal Counties; European NUTS 3 Coastal Region: a standard statistical regions (EU NUTS level 3), where at least half of the population is within 50 km of the shoreline. In the Irish case would include 7 of the 8 NUTS 3 regions in Ireland: the Border, the West, Dublin, the Mid-East, the Mid-West, the South East and the South West.

aquaculture, fisheries and shipping that require direct contact with the sea are more likely to be established close to the shore while industries such as marine commerce or marine advanced technology, that do not require direct contact with the sea have a lower percentage of enterprises next to the shore. This explains why some marine enterprises shown in the second map of figure 2 are further inland.

Figure 2. Density and distribution of Ireland's marine enterprises

The map on the left is a heat map showing the spatial distribution of Ireland's marine enterprises. The map on the right presents the actual distribution of Ireland's marine enterprises, overlaid on Irish coastal regions ranging from the Shoreline Electoral Districts to the EU NUTS3 spatial scales. Source: The Marine Institute/SEMUR Business Directory

It was also important to account for the fact that a marine enterprise could be located in one location (ED) but the workers could reside in other locations and commute to the enterprise on a daily basis. To adjust the model for this fact the Census of Ireland's Place of Work, School or College - Census of Anonymised Records (POWSCAR) database was used. In this database places of work, school and college are geo-coded and all workers represented in the Census are coded to their place of work while all resident students from the age of 5 and upwards are coded to their place of school/college. The data set also contains an industry grouping code where the type of business a resident is employed is grouped into one of eight

categories. A detailed microdata file containing the demographic and socio-economic characteristics of these residents along with information on the origin and destination of their journeys and the industry grouping they belong to was available for the analysis.

In summary there are three sources of data at three spatial scales that are used to generate marine workers in the spatial microsimulation process. The methodology, described in the next section, simulates individual marine workers at the electoral district (ED) level by making consistent marine industry employment statistics available at the national and county level, marine industry enterprise numbers at the ED level and POWSCAR industry groupings data that is also available at the ED level.

4. METHODOLOGY

The SMILE model uses a combinational optimisation technique called quota sampling to statistically match the Irish Survey on Income and Living Conditions (SILC)⁴ to small area population statistics from the Irish Census of Population. This generates a simulated dataset containing all the variables from SILC for the complete population of Ireland. Importantly the simulated observations in this new micro-dataset are representative of the small areas (the 3,409 EDs in Ireland) through the constraints of gender, education, age and ED population totals.

Quota sampling is a probabilistic reweighting methodology 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 (Farrell et al., 2013). As described by Hynes and O'Donoghue (2020) the quota sampling procedure analyses individuals grouped into households against constraints at either the individual or household level. Similar to the simulating annealing matching approach used by Hynes et al. (2010), quota sampling selects observations from a sample at random and considers whether they are suitable for admittance to a given small area population based on conformance with aggregate totals for each small area constraint.

Unlike simulating annealing, quota sampling only assigns individuals that conform to aggregate constraint totals and once an individual is deemed selected, it is not replaced. To accommodate this, small area aggregate totals for each constraint variable are designated as the initial values for what are termed 'quotas'. These quotas may be considered as running totals for each constraint variable, which are recalculated once a household is admitted to a small area population within the microsimulation process. This procedure continues until the

⁴ The Survey on Income and Living Conditions (SILC) in Ireland is a household survey covering a broad range of issues in relation to income and living conditions. It is the official source of data on household and individual income in Ireland.

total number of simulated units is equal to the small area population aggregates (i.e. all quotas have been filled).

More formally, and following O'Donoghue (2017), the quota sampling process involves the following steps:

For each individual n , a random number v is drawn

Individuals are sorted by v .

Individuals are then selected for the spatial sample (in this case an ED) if $x_{q,e}^{acc} + x_{q,n} \leq x_{q,e}^{total} \forall q$, where $x_{q,n}$ is the value of the variable q for the individual n , $x_{q,e}^{total}$ is the target total for ED e for variable q and $x_{q,e}^{acc}$ is the running total for variable q for ED e .

If $x_{j,e}^{acc} + x_{j,n} > x_{j,e}^{total}$ for any q , then the individual n is not used for the ED sample.

The simulated population for any given ED is selected when the total number of simulated units is equal to the ED aggregates (i.e. all quotas have been filled). As pointed out by O'Donoghue (2017) the variation of admitted units cumulates in a random sort which is consistent with aggregate constraint totals and the sampling without replacement results in significant efficiency gains of the quota sampling procedure over other methods.

O'Donoghue (2017) does however point out a number of convergence issues with this approach. He notes "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. 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."

In order to deal with these issues a number of validation techniques are used to ensure the synthetically created data are in line with various regional benchmarks for the variables used as constraints in the simulation process and for a number of the important non-constraining variables. Firstly, in-sample validation aggregates the simulated microdata for comparison with the regional benchmarks used to constrain the simulation to ensure the correct spatial distribution of the primary determinants of the matching process. The proportional correlation of each constraint variable used is compared to those in the census small area population statistics. Secondly, validation of the non-constrained variable of interest in the simulated data, disposable income, is carried out by comparing SMILE county-

level aggregates to county-level income statistics from the National Survey of Household Quality. Finally, a calibration procedure is used to align the disaggregated data within SMILE with known exogenous spatial distributions of disposable income and other key non-constraint variables in the SILC dataset⁵. The creation of the SMILE microsimulated dataset and the validation and calibration of the model results are fully described in Farrell et al. (2013).

The probabilistic reweighting process conducted for SMILE produces 4,327,959 individual records made up of the 11,557 records in the original SILC survey. While the SMILE model identifies the industry classification of each simulated individual those classifications are at a higher level of aggregation than that needed to identify workers across the marine industries. In order to generate an identifier for the marine industry that a simulated individual should work in, the information presented earlier detailing the employment numbers across the ocean economy industries from the Irish Ocean Economy Reports and the information from the Marine Institute/SEMRU Marine Industry Directory was utilised.

The steps followed in order to generate the spatial distribution of marine workers were:

Make the marine business directory data available at the ED level consistent with the marine employment data, available at the county level for the 12 marine industries.

Ensure that when aggregating the marine industries to the four relevant sector categories of the POWSCAR dataset (Agriculture, Forestry and Fisheries; Industry; Commerce; Financial and support services⁶) that the data is comparable with the POWSCAR Census Place of Work data that are already incorporated into the SMILE model.

Table 3. Linkages of sectoral structure across different data sources

Census (POWSCAR)	Place of Work	Marine Industry Enterprise Directory and Employment information
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⁵ The interested reader is directed to Edwards et al. (2011) for an in-depth discussion on calibration and the role of the constraint variables in the matching process and Whitworth et al. (2017) for a discussion on the accuracy of microsimulation models and the impact of the choice of constraints on model outcomes.

⁶ See note under table 3 for further breakdown of these four industry groupings.

<i>Electoral District</i>			<i>Electoral District for enterprise data/ County for employment data</i>
Agriculture, Fisheries	Forestry	and	Marine Aquaculture
Agriculture, Fisheries	Forestry	and	Sea Fisheries
Industry			Marine Advanced Technology Products and Services
Industry			Seafood Processing
Industry			Marine Manufacturing, Construction and Engineering
Industry			Marine Renewable Energy
Industry			Oil and Gas Exploration and Production
Industry			Marine Biotechnology and Bio-products
Financial and support services			Maritime Commerce
Commerce			Shipping & Maritime Transport
Commerce			Tourism in Marine and Coastal Areas
Commerce			Marine Retail Services

Agriculture, Forestry and Fisheries is POWSCAR industry grouping 1. Industry stands for POWSCAR industry grouping 2 that includes Manufacturing, mining and quarrying, Electricity, Gas, Water supply and Waste Management. Commerce is POWSCAR industry grouping 4 that includes Wholesale, Retail Trade, Transportation and Storage, Accommodation and Food Service Activities. Financial and support services stands for POWSCAR industry grouping 5 that includes Information and Communication, Financial, Real Estate, Professional, Administration and Support Service Activities.

In achieving these steps, the average employment for marine industry (i) per business (Bus) (within a county (c) was calculated, summing over all businesses at ED (e) level within the county to get the employment per business in the county:

$$Emp_{bus_{c,i}} = \frac{Emp_{c,i}}{\sum_e Bus_{e,i}}, i = 1 \dots 12$$

Multiplying this by the number of businesses in marine industry (i) in electoral district (e) level within the county to get a first round employment estimate per marine industry per ED:

$$Emp_{bus_{e,i}} = Emp_{bus_{c,i}} * Bus_{e,i}, i = 1 \dots 12$$

In order to be comparable with the POWSCAR data, the marine industries were collapsed to the 4 relevant POWSCAR industry groupings (j):

$$Emp_{bus_{e,j}} = \sum_i Emp_{bus_{e,i}}, j = 1, 2, 4, 5$$

There are sometimes data inconsistencies, where there are fewer workers in the POWSCAR industry grouping (j) in the ED than identified in the marine industry totals for that ED which based on the match between the business directory data and the aggregate marine employment estimates per county. Where this occurs, the POWSCAR total was used to constrain the number of workers in the industry.

$$Emp_{bus_{e,j}}^* = \min(Emp_{bus_{e,j}}, Emp_{bus_{e,j}}^{POWSCAR}), j = 1, 2, 4, 5$$

Resulting sometimes in a difference

$$Emp_bus_{e,j}^{diff} = Emp_bus_{e,j} - Emp_{bus_{e,j}}^*, j = 1, 2, 4, 5$$

This difference is allocated across other EDs in the county that have a positive number of workers in the j level industry grouping until the whole difference is allocated, to produce a new total $Emp_bus_{e,j}^{**}$, ensuring consistency between county level marine industry employment totals and POWERSCAR ED employment data.

Then $j(i)$ level allocation is reconverted to (i) level:

$$Emp_bus_{e,i}^{**} = Emp_{bus_{e,j}}^{**} \cdot Emp_bus_share_{e,i}$$

where $Emp_bus_share_{e,i}$ is the share of marine industry (i) employment in POWERSCAR industry j in ED e .

Once the population of marine industry workers were established in the SMILE model the next step was to use the data to analyse the impact of an economy wide shock on the spatial distribution of employment in the Irish ocean economy. Given the current interest in the impacts of the Covid-19 (Coronavirus) pandemic on the economy it was decided to use the adjusted SMILE model to analyse this issue from the perspective of marine sector employment⁷. Individuals who lost their jobs as a result of the Covid-19 crisis were eligible for a Covid-19 Pandemic Unemployment Payment (PUP). This scheme provided a payment of €350 per week, available to workers who have lost respectively their job on (or after) March 13th, 2020 due to the Covid-19 pandemic or who have fallen sick.

Data on the numbers in receipt of these payments across 17 industrial classes was available for the analysis for the dates between March 13th and May 18th 2020 from pandemic unemployment payment statistics provided by the Irish Department of Employment Affairs and Social Protection (DEASP)⁸. The numbers and type of individuals eligible for payment and directly affected by the crisis in the SMILE model were simulated using the PUP

⁷ Others have also being interested in using microsimulation techniques to examine the impact of Covid-19 on the Irish economy. Using a dynamic calibrated microsimulation approach O'Donoghue et al. (2020) combine 'nowcasting' methods that employ up-to-date data from live registers, official reports on the labour market and policy impacts of Covid-19 with the Labour Force Survey and a household income generation model, to predict the distributional impact and the fiscal costs of the Covid-19 crisis in Ireland.

⁸ <https://www.gov.ie/en/publication/f4c60c-covid-19-statistics/>

statistics that are available by county and by industry. In order to generate the numbers of marine workers in receipt of the PUP by county and industry, an iterative proportional fitting procedure (Wong, 1992) was used. Beginning with a starting value of employment reduction proportional to the employment share by industry and county, the numbers out of work due to Covid-19 both in a county and by industry were imputed to be consistent with the PUP control totals. It is assumed that the decline in employment in each marine industry per county is pro-rata to the county level decline in the POWSCAR industry grouping it belongs to.

5. RESULTS

On completion of the linkages outlined in the methodology section the synthetic population in the SMILE model now contains marine industry employment related identifiers for all individuals specified as being in the ocean economy. Figure 3 shows the simulated employment numbers in the ocean economy broken down by county. The aggregate figures match up to the totals by marine industry from the national ocean economy statistics from SEMRU (2019). This is achieved by design given the data produced by the SMILE uses the employment figures presented in the ocean economy report as an aggregate constraint in the simulation process for each of the marine industries. The largest concentration of ocean economy workers are based in the Greater Dublin Area⁹. Dublin City alone contained 12.5% of the individuals in the dataset, followed closely by Cork County (11.6%) and Donegal County (9.9%). Dublin County as a whole (the sum of workers residing in Dublin City, Fingal, South Dublin, and Dun Laoghaire-Rathdown), contained over a fourth of ocean economy workers (27.4%).

⁹ The Greater Dublin Area as defined by the Dublin Transport Authority Act of 2008 is an aggregate area comprising the city of Dublin and the administrative counties of South Dublin, Fingal, Dún Laoghaire-Rathdown, Kildare, Wicklow and Meath
<http://www.irishstatutebook.ie/eli/2008/act/15/section/3/enacted/en/html#sec3>

Figure 3. Total estimated marine employment by county.

The density map of overall marine industry employment at the ED spatial scale shown in figure 4 suggests that there are clusters of marine employees in areas close to the major ports in the northwest, southwest, and southeast of Ireland. Figure 5 displays the simulated employment across the 12 marine industries by ED of residence. This more detailed breakdown of simulated employment by marine industry confirms once again that the residency of those employed in industries that require direct contact with the sea such as fisheries, aquaculture, and oil and gas exploration are very concentrated in coastal areas. However, industries such as marine advanced tech, marine manufacturing and marine bio-tech display a much greater spatial distribution. Seafood processing and sea fisheries workers are, as expected, located close to the major fishing ports, and can be seen from the map to be particularly concentrated in EDs surrounding Killybegs fishing harbour in Co. Donegal and Castletownbere fishing harbour in Co. Cork. These are the two biggest pelagic fishery harbours in the country.

Figure 4. Estimated marine employment by electoral district

In line with the aggregate estimates for employment reported by SEMRU (2019) marine tourism alone accounts for 53% of all marine workers produced in the microsimulated data, with 18,184 employees across the country. Marine tourism and leisure employees would appear to be more concentrated around Dublin on the east coast but are more evenly spread along the shoreline EDs down the west coast (the largest number of simulated workers in this industry reside in the Greater Dublin Area, with 29% residing in Dublin County (as opposed to 10% in Cork and 7.5% in Kerry)). The even spread of marine tourism employees along the western seaboard may reflect the presence of the popular Wild Atlantic Way tourism trail that runs down that coastline and the many popular marine related attractions along the route such as the Cliffs of Moher in County Clare which is usually the second most popular tourist attraction in the country with overseas visitors (Fáilte Ireland 2019).

Figure 5. Employment in marine industries by electoral district of residence.

Having generated the marine workers per ED using the spatial microsimulation approach the next step was to use the model to analyse the spatial impact of a policy or disruption to a marine industry or to the sector as a whole. With that in mind the Covid-19 pandemic provided a unique opportunity to examine what impact such an all-encompassing shock has had on employment across the ocean economy industries. Table 4 shows the proportional reduction in employment as of May 18th 2020 due to Covid-19 crisis by county and broad industrial grouping. As discussed in the previous section this is based on those individuals in each sector that are in receipt of the Covid-19 PUP on that date.

According to the figures from DEASP the impact of the crisis was most felt over this period by those working in the Accommodation and Food Service activities (124,500 individuals in receipt of PUP), followed by Wholesale and Retail Trade (88,400 individuals in

receipt of PUP) and Construction (76,600 individuals in receipt of PUP). As shown in table 4 the figures for the construction industry appear highest per county but this is due to the fact that in the POWSCAR industry classification system the tourism elements of accommodation and food service activities are absorbed within a category that also includes wholesale, retail trade, transportation and storage activities which masked the true impact of the pandemic on the marine tourism and leisure industry in the statistics below.

The estimated proportional reduction in employment for marine tourism and leisure is therefore less than what would be observed for the tourism sector in Ireland overall. However, the relatively large proportional decrease in tourism observed for counties Kerry, Galway, Clare and Donegal is in line with observations from Hynes et al. (2019) where a survey of marine and coastal tourists in Ireland indicated that overseas visitors in particular undertake the majority of their coastal and marine related activities on the West Coast of Ireland. In the study County Kerry, County Galway and County Clare were the leading counties, in that order, for participation by overseas tourists in coastal and marine tourism activities. In a subsequent report a similar pattern was also observed for domestic tourism (Hynes et al. 2020). The large proportional drop in construction activity is relatively balanced across counties while the lowest impact of the pandemic would appear to have been on those working in the three categories of Agriculture, forestry and fishing; Education, human health and social work activities and Public administration and defence, compulsory social security, respectively.

Table 4. Estimated employment reduction (proportion) as of May 18th 2020 due to Covid-19 crisis by county and POWSCAR industry grouping.

POWSCAR Industry Grouping*	1. Agriculture, Forestry and Fisheries	2. Industry	4. Commerce	5. Financial and support services
Carlow County	0.102	0.188	0.474	0.175
Cavan County	0.076	0.139	0.361	0.140
Clare County	0.089	0.161	0.429	0.157
Cork City	0.079	0.144	0.371	0.124
Cork County	0.079	0.144	0.371	0.124
Donegal County	0.084	0.150	0.430	0.139

Dublin City	0.085	0.148	0.355	0.131
South Dublin	0.085	0.148	0.355	0.131
Fingal	0.085	0.148	0.355	0.131
Dun Laoighe	0.085	0.148	0.355	0.131
Galway City	0.101	0.185	0.466	0.156
Galway County	0.101	0.185	0.466	0.156
Kerry County	0.092	0.165	0.498	0.156
Kildare County	0.076	0.136	0.332	0.130
Kilkenny County	0.072	0.131	0.335	0.125
Laois County	0.078	0.138	0.353	0.139
Leitrim County	0.074	0.133	0.368	0.131
Limerick City	0.088	0.160	0.401	0.148
Limerick County	0.088	0.160	0.401	0.148
Longford County	0.095	0.174	0.425	0.169
Louth County	0.095	0.171	0.433	0.175
Mayo County	0.101	0.184	0.478	0.177
Meath County	0.081	0.144	0.363	0.147
Monaghan County	0.078	0.142	0.356	0.151

Offaly County	0.091	0.164	0.413	0.161
Roscommon County	0.097	0.176	0.421	0.171
Sligo County	0.098	0.179	0.455	0.169
North Tipperary	0.095	0.173	0.424	0.168
South Tipperary	0.095	0.173	0.424	0.168
Waterford City	0.090	0.167	0.437	0.146
Waterford County	0.090	0.167	0.437	0.146
Westmeath County	0.096	0.175	0.440	0.154
Wexford County	0.092	0.167	0.444	0.161
Wicklow County	0.084	0.150	0.384	0.134

* POWSCAR Industry Groupings: 1. Agriculture, forestry and fishing, 2. Manufacturing, mining and quarrying, Electricity, Gas, Water supply and Waste Management, 4. Wholesale, Retail Trade, Transportation and Storage, Accommodation and Food Service Activities, 5. Information and Communication, Financial, Real Estate, Professional, Administration and Support Service Activities

([https://www.cso.ie/en/media/csoie/census/census2016/powscar/Place_of_Work_School_or_College_-_Census_of_Anonymised_Records_\(POWSCAR\)_User_Guide_2016_v4.pdf](https://www.cso.ie/en/media/csoie/census/census2016/powscar/Place_of_Work_School_or_College_-_Census_of_Anonymised_Records_(POWSCAR)_User_Guide_2016_v4.pdf))

The numbers and type of individuals eligible for payment and directly affected by the crisis in the SMILE model were simulated using the PUP statistics that is available by county and by industry category¹⁰. As described in the previous section the numbers in receipt of PUP across the marine sectors by ED and by county were simulated and the resulting impact by county is shown in table 5. Based on the simulation process 32% of marine workers are estimated to have been in receipt of the Covid-19 PUP as of May 18th 2020. According to the results tourism in marine and coastal areas and marine retail services saw the greatest reduction in employment due to the pandemic while aquaculture saw the lowest impact. This

¹⁰ The PUP statistics are available at the country level for 17 industry categories. The relevant categories had to be first collapsed to match the 4 POWSCAR industry groupings shown in table 4.

latter finding however is misleading as aquaculture was under the industry classification of Agriculture, forestry and fishing. The relatively small contribution of aquaculture to total employment in the Agriculture, forestry and fishing classification overall coupled with the relatively low impact of the pandemic on employment in agriculture means that the proportion made unemployed in this marine industry is likely to have been underestimated.

Table 5. Simulated Covid-19 unemployment impact per ocean economy industry

	Not receiving the Covid Unemployment Payment	Receiving the Covid Unemployment Payment	Total	Covid Rate
Marine Aquaculture	1796	173	1969	0.088
Sea Fisheries	2183	419	2602	0.161
Marine Advanced Technology Products and Services	530	96	626	0.153
Marine Manufacturing, Construction and Engineering	707	125	832	0.150
Oil and Gas Exploration and Production	132	22	154	0.143
Seafood Processing	2023	368	2391	0.154
Marine Renewable Energy	393	60	453	0.132
Marine Biotechnology and Bio- products	502	89	591	0.151
Maritime Commerce	285	43	328	0.131
Shipping & Maritime Transport	3140	1900	5040	0.377

Tourism in Marine and Coastal Areas	10839	7345	18184	0.404
Marine Retail Services	559	377	936	0.403
	23173	10933	34106	

Although sea fisheries is also included in the Agriculture, forestry and fishing category a special request to DEASP resulted in a more accurate figure being supplied for those in receipt of the PUP specifically employed in sea fisheries. This figure demonstrated that the impact on employment in the fisheries sector due to the pandemic was, as expected, higher than suggested in the broader grouped category of Agriculture, forestry and fishing although it should be kept in mind also that some of the fleet would have been tied up at this time of year anyway, being in between targeted runs for different species of fish.

By simulating those in receipt of the Covid-19 PUP the spatial microsimulation approach provides a more spatially accurate picture of the impact of the crisis on the marine industries than is possible with the county level statistics available from the national statistical agency or DEASP. As shown in figure 6, the use of the SMILE marine model allows for the mapping of the proportional reduction in employment as of May 18th 2020 due to the Covid-19 Crisis by marine industry at the ED spatial scale. These proportions are at the individual ED level, and represent the ratio of the number of marine related workers who are receiving the Covid PUP to the number of marine related workers residing in the ED before the pandemic hit. As can be seen in figure 6, most shoreline EDs faced some level of proportional reduction in marine related employment – typically varying between 20%-60%. However, all along the coastline EDs presenting with 60%-80% reduction in marine employment are not uncommon. The map also presents EDs inland which feature large reductions in marine related employment. This can be explained by the relative scarcity of marine related workers as distance from coastal EDs increases, so even a small number being made unemployed will mean a large proportional decrease in the particular industry for these inland EDs.

Total Marine COVID-19 Unemployment

Figure 6. The proportional reduction of marine related employment in Ireland due to the COVID-19 Crisis

Figure 7 provides a more detailed breakdown of the spatial impact of the crisis on ocean economy employment across the 12 marine industries by ED of residence. Similar to the wider economy the customer-facing industries of the ocean economy, such as marine tourism and leisure services and marine retail, have in general been the most affected by the measures implemented by the Irish Government to contain the pandemic. Counties in the west of Ireland have been particularly affected due to the fall in marine tourism activity with 60% reductions observed in popular coastal tourism and leisure areas, such as west Cork, Kerry, Galway, Mayo, and Donegal. This is in line with findings from Lydon and McGrath (2020) who note that the concentration of jobs in consumer-facing sectors such as general tourism and accommodation along the Western ‘Atlantic Economic Corridor’ means that workers in these coastal counties have been adversely affected by public health restrictions compared to other parts of Ireland. The authors further point out that it is likely to be younger and female workers who are particularly vulnerable to employment shocks in this sector and that is likely to hold true for the marine tourism and leisure industry as well. As shown in the figure the

east coast also faced reduction in employment for this industry, especially surrounding the greater Dublin area and its commuting basin.

Figure 7. The simulated proportional reduction of employment in Ireland due to the COVID-19 crisis across marine industries.

The simulation process suggests that nearly 38% of the shipping and maritime transportation sector was in receipt of the PUP unemployment benefit in mid-May 2020 while marine retail services has the third highest COVID related unemployment rate (see Table 5) with just over 40% of the sector receiving the COVID payment. The employment impacts on

shipping and port activity are particularly evident in Cork and Dublin which are home to the largest of Ireland's ports. The marine manufacturing, construction, and engineering sector saw relatively low rates of COVID unemployment while the marine renewable energy sector was among the least affected by the COVID pandemic based on the microsimulation results, with 60 of the 453 workers in this sector receiving the COVID unemployment payment.

6. CONCLUSIONS

Similar to other coastal countries, marine systems contribute significantly to the Irish economy, playing a role across multiple sectors such as communications, transportation, energy, and food. The shifting nature of the economic landscape provides opportunities and challenges for those who operate in the ocean economy. If sustainable growth is to be achieved effectively, then there is a need for tools that can analysis the impact of policy change or other drivers of change on the sector. The spatial microsimulation approach described in this study allows the analyst to add a spatial dimension to impact assessment of the ocean economy at a local district, household, or individual-level. This provides a regional level of analysis not generally possible when dealing with ocean economy statistics that are often even difficult to compile at a national level and offers a powerful modelling tool for maritime spatial planning.

The microsimulation model used in this analysis, can therefore aid in the development of marine policy by increasing the granularity of available data. The ability to predict the impact of social and economic policies at micro- and macro-levels is especially useful for the ocean economy which has industries (such as tourism or fisheries) that can dominate rural areas. In the analysis presented here the spatial microsimulation model facilitated a unique look into the specific distribution of employment in the Irish ocean economy both before the Covid-19 pandemic and after the first wave of the Covid-19 pandemic in Ireland. Of the 34,106 ocean economy workers in the synthetic dataset, nearly a third (32%) are estimated to have received the Covid-19 PUP Payment as of May 18th 2020. The resulting maps also demonstrate that many of those made unemployed were outside the main urban centres particularly in the case of marine tourism and leisure and the natural resource based industries.

It would also be useful to get more accurate data on the rate of the PUP payments for certain industries in the impact analysis. As previously discussed the impact of the pandemic is likely to be underestimated for aquaculture as the share of those receiving the payment in the broader classification of 'agriculture forestry and fishing' is used as the share for this industry. The impact on marine tourism and leisure is likely to be underestimated for similar reasons. On the other hand it is likely to be overestimated for the shipping and maritime transport industry given the estimates are based on an industrial classification that also includes food and accommodation services. Some ground-truthing of these estimates through discussion with the representative associations in each case would be beneficial to assess the levels of discrepancy.

In terms of future research it would be interesting to link the spatial microsimulated data to marine ecosystem service benefits that are either generated as a result of the industry activity (e.g. cultural ecosystem services associated with fishing communities or water filtration services associated with shellfish aquaculture) or that are reduced in supply (e.g. reduced biodiversity levels by overfishing, increased carbon dioxide release due to the continued extraction of oil and gas or the loss in societal welfare due to the degradation of seabed habitats from bottom trawling). In doing so a more holistic viewpoint could be gained of the sustainability of the growth paths of the ocean economy industries.

It has been made increasingly evident that economic shocks brought on by events like the recent Covid-19 crisis can have dramatic local level impacts, and the utilization of the spatial microsimulation can facilitate a more evidence based policy response in terms of industry and regional specific supports and can also inform more effective marine planning. While the focus of the analysis here was on the distribution of the ocean economy employment figures, the model also produces a highly detailed population of marine workers exhibiting more socio-economic characteristics of interest, including estimated income, age, sex, education, etc. While synthetic, these additional characteristics provide a solid foundation for future research that could inform the development of local, national, and international marine policy surrounding the sustainable development of the Irish ocean economy.

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