The Spatial Distribution of Welfare in Ireland

A thesis submitted in fulfilment of the degree of
Doctor of Philosophy

By

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Description of Thesis

In this thesis welfare is examined in a spatial context. A broader definition of welfare is taken so that it includes more than just income. In-kind benefits, indirect costs, life-satisfaction, locational effects are all examined in a spatial context. The impact of these welfare drivers on the spatial distribution is examined with each chapter focusing on a different welfare driver. Differences between areas may be psychical (e.g. climate) or structural (e.g. high education attainment) using a spatial approach can account for some of this variation. An interaction exists between space and the economy which results in agglomeration economies and clustering based on social class. However, there are market failures (e.g. congestion) which can reduce welfare. A broader measure of welfare which includes additional components and not just monetary income acknowledges the spatial heterogeneity that exists across space. A small area examination allows for pockets of deprivation and poverty to be identified. Some of the reasons behind the inequality that exist between and within areas is explored and described. Taking each component in isolation has the power to show the effects of that driver on welfare.

International studies are often limited by a lack of income data at a small area level. This thesis uses the output from a spatial microsimulation model to overcome the lack of income data at a spatial scale. This income data is enhanced through a data fusion process to create and include additional spatially rich welfare data. Spatial methods such as interpolation and network analysis tools are utilised to calculate and create new small area datasets. Mapping tools such as GIS provide the added benefit of displaying results in an effective way. This newly created data can be used to calculate how welfare varies spatially depending upon the definition of welfare used.

The broader definition of welfare adopted is based on conceptual underpinnings that any benefits/costs which increase/decrease individual potential to consume should be included in a measure of welfare. Drivers of welfare examined include intertemporal effects, housing, commuting, labour markets, spatial attributes and exposure to flooding. The sensitivity and impact of each component on individual welfare is examined. By using a spatial approach differences in the impact of each driver across space can be measured. Due to the heterogeneous nature of welfare, some drivers can have positive benefits in some areas but negative in others. By adopting a spatial approach these differences can be identified.

Measuring welfare at a disaggregated spatial scale is required before we attempt to understand why the spatial distribution of welfare looks the way it does. Research such as this is crucial to evaluate and recommend policies that improve welfare and reduce spatial inequalities. Due to their limited nature, identifying areas with greater "need" allows resources to be targeted more efficiently. This thesis makes a number of recommendations in this regard as to why policy should adopt a more holistic approach to welfare. It highlights particular challenges in the area of data collection and the need for greater focus on spatial impacts of various policy measures at a small area level.

Preface

This PhD research was funded through the John and Pat Hume Scholarship.

In each chapter I acknowledge collaborating partners and co-authors. In all models I made a major contribution to the development. Most of the analysis in this thesis extends work done in collaboration with my supervisors and academic researchers. In the case of chapter 2.1, 2.2 & 5, the first collaborator is the lead author in the chapter reflecting their contribution to the chapter. In the remaining chapters I am the lead author.

In chapter 2 my contribution is providing an updated version of the SMILE model to include an intertemporal, housing, commuting and local environmental characteristics component.

In chapter 5, I calculated the OD cost matrix and generated all of the maps included in the paper. I calculated the journey times and distances and the costs associated with each.

The methodology section 6.3 is adapted from O'Donoghue (2013)

The research from chapter 8 has been funded by the Environmental Protection Agency, and forms part of a larger research project, based at UCC and in collaboration with the Grantham Research Institute on Climate Change and the Environment at the London School of Economics, which aims to estimate costs of climate impacts for Ireland and explore policy responses for managing climate risks, with a particular focus on the issue of flooding.

Statement

I Paul Kilgarriff confirm that the work submitted is my own and that appropriate credit has been given where reference has been made to the work of others. This work has not been submitted in any form for another degree or diploma at any other university or institution of tertiary education.

Signed:

Date:

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The processes of researching and writing a PhD thesis can be a lonely and sometimes isolated experience, yet the support, knowledge and expertise of others is vital. To this end there are a number of people I wish to thank for helping to bringing this process to an end.

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Abbreviations

CEDRA	Commission on the Economic Development of Rural Areas
CBI	Central Bank of Ireland
CPI	Consumer Price Index
CSO	Central Statistics Office, Ireland
DECLG	The Department of the Environment, Community & Local Government
ECHP	European Community Household Panel
ED	Electoral Division
ESRI	Environmental Systems Research Institute[1]
EuroMOD	Tax-benefit microsimulation model for the European Union
FDI	Foreign Direct Investment
GDA	Greater Dublin Area
GDP	Gross Domestic Product
GIS	Geographic Information System
GNP	Gross National Product
HAP	Housing Assistance Payment
IR	Imputed Rent
LII	Living in Ireland (survey)
LPT	Local Property Tax
NEG	New Economic Geography
NRA	National Roads Authority

[1] Makers of ArcGIS Desktop

NSS	National Spatial Strategy
NTA	National Transport Authority
NUTS	Nomenclature of Units for Territorial Statistics level (1, 2, 3)
OD	Origin Destination
OSi	Ordinance Survey Ireland
POWSCAR	Place of Work, School or College - Census of Anonymised Records
QS	Quota Sampling
R	Statistical Software Package
RPPI	Residential Property Price Index
SA	Small Area
SAPS	Small Area Population Statistics
SILC	Survey on Income and Living Conditions
SMILE	Simulated Model of the Irish Local Economy
STATA	Statistical Software Package
SVTT	Subjective Value of Travel Time
VAT	Value Added Tax
VoT	Value of Time

Chapter 1. Introduction

This thesis will examine the spatial distribution of welfare in Ireland. A broader more holistic definition welfare is adopted which includes intertemporal, commuting, housing, local labour markets, spatial attributes in addition to household disposable income. Welfare is examined at detailed spatial scale so that differences between areas can be examined. Using a spatial approach requires the use of spatial analysis and geocomputation methods in order to collate and create new disaggregated spatial data. The disposable income measure which is at a small area level is improved upon to include more than just income. Each driver of welfare can be examined in isolation.

To be able examine the sensitivity of the drivers of welfare at a detailed spatial scale detailed spatial data is required. There is a lack of detailed welfare data at a small area level on aspects such as income, housing, commuting, agriculture and life-satisfaction. Geocomputation and spatial analysis techniques are utilised to gather and create new small area datasets. Monetary and non-monetary aspects of welfare in addition to space are combined in the one model. In so doing it is possible to show how these additional aspects of welfare can have a significant impact on an individual/household/area overall level of welfare.

Examining the spatial distribution of welfare is a complex task. There are a number of factors which can influence welfare; this can be within and between regions or how welfare is defined. Welfare can consist of both monetary and non-monetary components. In order to fully understand the distribution of welfare, an approach is taken which is spatial in nature and uses both monetary and non-monetary measures to define welfare. Adopting this approach allows monetary and non-monetary drivers of welfare to be examined both between and within areas. The sensitivity of the spatial distribution of welfare to each measure can also be tested. There is not one single definition of welfare, therefore it is important to set out the conceptual framework. How does one define welfare in this thesis? The following paragraphs outline how welfare is defined.

Welfare may be defined using monetary and non-monetary aspects (Barr, 1998). Monetary aspects can include income and wealth. Income can be derived from a number of sources such as:

- Work income by selling one’s labour for money

- Income from wealth, e.g. share dividends
- Social transfers from being unable to work due to illness or not having employment
- Non-cash income, e.g. company car

Non-cash income includes in-kind benefits, such as the benefit one derives from consuming an asset such as a house (UN, 2011). There are also time costs such as commuting which reduce leisure time. Individuals can increase utility through their use of leisure time. Anything which decreases the amount of leisure time available will therefore decrease utility.

Welfare is examined in a spatial context to account for differences between and within areas (Kanbur and Venables, 2003). These differences may hold advantages or disadvantages for an area (Fujita et al., 2001). They may be psychical in nature; such as a better climate, environmental amenities, natural landscapes or soil quality. They may also be structural; such as an educated workforce, agglomeration economies, diseconomies (congestion, pollution), local labour markets, local policies, public service provision and other private services (Krugman, 1998) specific to an area. By measuring welfare across place, a lot of this variation is captured.

Related to examining welfare between and within area is the unit of analysis. The output from a spatial microsimulation approach is used which allows welfare to be examined at an individual, household and small area level (O'Donoghue et al., 2013a). This level of spatial disaggregation enables welfare to be examined spatially between areas, and also within areas between people. The composition of the household is also accounted for in this model. Accounting for household size can have a significant impact on a measure of welfare (Atkinson et al., 1995).

Non-monetary drivers of welfare are more difficult to define. These drivers can be measured through an individual’s well-being, happiness or life-satisfaction. These measures are influenced by aspects specific to the individual such as their socio-demographic characteristics (Blanchflower and Oswald, 2004) or local environment (Van Praag and Baarsma, 2005, Roback, 1982). Non-monetary indicators can help to supplement monetary income indicators (Atkinson et al., 2004, Nolan and Whelan, 2010).

In order to examine the spatial distribution of welfare, both monetary and non-monetary aspects are included. To examine welfare between and within area, a spatial component is added and individual and household level data is used. Welfare can be broken down into its components, analysed across place and the effect of each measure on the distribution can be quantified. This will add to our overall understanding of welfare.

1.1 Theoretical Framework

Before welfare can be measured, a definition of welfare is required. The complexity and numerous approaches which can be taken to measure welfare, require a strict definition. We must decide upon what to include and what to leave out when measuring welfare. This raises a number of questions:

- How should welfare be measured?
- How is welfare defined?
- Will we use market income, disposable income, expenditure or wealth to define welfare?
- What monetary and/or non-monetary aspects are used to define welfare?

Indicators of poverty and deprivation are typically measured using disposable income or market income (Nolan and Whelan, 2010). This definition takes disposable income as a proxy for consumption. Such a definition however fails to account for other non-monetary consumption which takes place such as from durables like housing. Income may only represent potential spending power (Atkinson, 1983). A person who saves some of their income is postponing consumption for a later date; smoothing consumption over time (Friedman, 1957).

> "Income in a given period is the amount a person could have spent while maintaining the value of his wealth intact" - (Atkinson, 1983)

An individual's income is therefore raised if their potential to consume is increased. Anything that increases that potential should be considered in the measure of welfare. Barr (1998) provides us with a framework around which individual welfare can be defined. Individual welfare can consist of:

- Physical wealth in the form of consumer durables; such as a house or car

- Financial wealth, including shares or government bonds
- Human capital, person's level of skills

Both monetary and non-monetary income can be derived from each of these three sources. Physical wealth provides non-monetary welfare in the form of consumption value derived from living in a house. Physical wealth can also provide monetary income such as the income a landlord receives by renting a house. Financial wealth provides monetary income, such as share dividends. Human capital produces several streams of income both monetary and non-monetary. Firstly, a person can sell their skills and time for a wage. They can also receive non-monetary benefits from selling labour, in the form of job satisfaction which can be both positive and negative. An individual also has leisure time from which they derive non-monetary income (Barr, 1998). Such a conceptual definition of income differs from much of the statistical data on the distribution of incomes (Atkinson, 1983). These sources typically define income in the same way as for income tax purposes (Eurostat, 2017).

A comprehensive measure of welfare will therefore account for the consumption value derived from consumer durables such as housing (Smeeding and Weinberg, 2001). A homeowner will derive in-kind benefits from living in a house that they own. Being an owner occupier does not provide a rental income, however it saves the owner from having to pay market rent (Atkinson, 1983). This market rent saved is known as imputed rent. By not paying market rent an owner occupier's potential to consume increases. This benefit in-kind should be included in the measurement of welfare (UN, 2011). In contrast households who are not owner occupiers experience the costs of providing housing. In the case of private renters these costs often exceed the benefits.

Household composition will impact on how welfare is measured (OECD, 2013b). This particularly applies to monetary income. Typically in a household a level of income-sharing occurs. Equivalent scales are typically used to account for this income-sharing. Dividing income equally across all members of the household would not be the correct method, as it fails to account for different needs depending on age. Also any economies of scale would not be accounted for. Adult equivalent scales allow comparison between households and at the same time take into account the units that make up the household composition (Atkinson, 1983). They apply a weight to a household member based on their age and number of total household members (Callan et al., 1996a).

Commuting will have monetary and non-monetary impacts on welfare. Monetary costs of commuting will depend upon the mode of transport and distance travelled. This time spent commuting will reduce the amount of leisure time available for other activities and therefore has an opportunity cost (Becker, 1965). Related to commuting will be the importance of place. Where a person lives is a large determinant on whether they work, where they work and how much they earn for working. There will be a trade-off between commuting and housing costs (Kain, 1962). Rural residents may trade-off lower housing costs for lower wages and lower commute times in the same way urban dwellers may accept higher housing and commute costs in exchange for higher wages (So et al., 2001). In addition to this trade-off there are other important determinants around where an individual chooses to live.

There are also other non-monetary welfare components which impact through space. Spatial attributes of the area can impact on all forms of income both monetary and non-monetary (Roback, 1982). Distance will impact on access to labour markets and either increase or decrease a person's probability of finding employment. Space also impacts on the cost of housing and related to this is commute time and distance. There are other spatial attributes of the environment from which individuals can derive utility from, such as the crime rate or environmental attributes of the region. Given the interaction between welfare and space, welfare will vary both within and between districts (Bourguignon and Morrisson, 2002). Space interacts with a number of components of monetary and non-monetary welfare.

Spatial Context

Welfare is examined in a spatial context as welfare is not homogenous across place (Dall'Erba, 2005). Welfare will vary due to underlying differences between areas. Areas experience different labour markets, land prices, education levels, population density, environmental characteristics, climate, level of infrastructure, service provision and access levels. Introducing place will begin to take into account these differences.

Von Thünen (1826) was one of the first to recognise the interaction between spatial analysis and the economy; in Von Thunen's model, land rent is a function of yield per unit of land and transport costs (which is a function of distance). This land rent will be a function of the level of competitive advantage in using the land productively (Ricardo, 1821). This recognises the level of spatial differences that exist in an economy.

Launhardt (1885) & Weber (1909) adopted a least cost theory approach to industrial location. Historically firms have located where materials, labour and transportation costs are all minimized.

The growth and increasing importance of globalisation saw the emergence of the “new economic geography” (NEG) (Krugman, 1998). The NEG aids in explaining the uneven spatial development that exists. Lower transport and communication costs are driving economic development in rural areas. Agglomeration economies cause industry to cluster together leading to aspects such as lower transport costs, economies of scale and market size (Krugman, 1991). The NEG uses a core periphery model. This will lead to a concentration in an area which can increase land rents making it unaffordable for residential and causing urban sprawl (Brueckner, 2000). Limited supply of land means it must be used optimally (Henderson, 1974). Expanding cities also encroach onto agricultural land causing demand pressures.

More recently in advanced economies it has become more difficult to spot industry concentrations as they have become more subtle. Tangible forces of NEG are also not as powerful in explaining localisation. The no-dormitive-principles are more difficult to hold with invisible external economies such as information spillovers being more relevant compared to transport costs (Krugman, 2011). Technological advances have made some of these transport costs, costless in some industries. Even without physical differences between areas there are differences that can arise due to these spillovers, thick market effects or linkages between firms (Kanbur and Venables, 2003). In addition to agglomeration economies, industrial concentrations may also be influenced by government intervention (Van Egeraat, 2006). These models around firms and industry help explain why some areas are more industrialised or urbanised than others.

There are a number of drivers of welfare which vary depending upon location such as housing, commuting and environmental characteristics. House prices interact with the environmental characteristics of the area but also the economic characteristics of the area (Rosen, 1974). The economic performance of a region can have a significant impact on house prices and may lead to affordability issues and urban sprawl. Rich (poor) regions tend to cluster close to rich (poor) regions (Dall’Erba, 2005). Affluent areas tend to have higher house prices compared to poorer areas and will value characteristics differently (Zietz et al., 2008). House characteristics and other amenities can influence the value of a house (Mayor et al., 2012). The NEG can help explain why land prices are higher in cities (Krugman, 1991). Limited resources such as land and concentration of activity especially around cities leads to an increase in demand for land and hence higher land rents (Krugman, 1998). There will however be point beyond which individual welfare will decrease as population increases (Henderson, 1974). Diseconomies such as commuting will cause tensions between city size and utility leading to an optimum city size. Market failures such as congestion and clustering will lead to inefficient outcomes (Kanbur and Venables, 2003).

Defining Welfare Spatially

Attempting to capture the welfare of an individual and household will include both monetary and non-monetary components (Nolan and Whelan, 1996). Taking into consideration more than just income, enables us to measure other aspects of welfare such as life-satisfaction. Introducing space into the measure of welfare allows comparisons to be made between areas. Incomes can be further disaggregated based on where they are located. Similarly time enables welfare to be examined across periods. Combining time, space and welfare provides more information and a greater understanding of welfare.

Using the output from a spatial microsimulation approach allows us to estimate welfare at a small area level (Chin and Harding, 2006). When there is a lack of income information in census data, spatial microsimulation enables us to overcome this difficulty, by making use of income data from surveys. Whereas census data contains spatial data, it contains no information on income. Survey data however contains income information but does not have a spatial component. Spatial microsimulation links the two data sources to overcome the lack of data in each (Morrissey and O'Donoghue, 2013).

The spatial distribution of income estimated using spatial microsimulation is the base measure of welfare used. This measure of welfare is estimated at the small area level and linked to individuals and households. This enables welfare be examined between and within areas (Rey, 2004). Utilising this base measure of welfare, further elements are added. An intertemporal analysis of welfare is conducted. Not only will welfare vary across place but also across time (Fan and Casetti, 1994). A changing economic climate and other local policy decisions over time, will impact in different ways (Conceição and

Ferreira, 2000). Some areas may be more resilient than others, by having a higher skills base, industry diversification and greater access (Ballas and Clarke, 2001).

In this thesis the following components of welfare are all examined in a spatial context:

- Income
- Intertemporal income
- Commuting
- Housing
- Labour Markets
- Happiness

Another element of welfare worth considering in a spatial context will be housing (UN, 2011). Both rental values and property prices vary depending on area (Lyons, 2017b). Hedonic pricing estimates a property's value based on a bundle of attributes which includes location (Rosen, 1974). The imputed rent one receives by living in an owner occupied house can have a significant impact on the income distribution (Frick and Grabka, 2003). Net imputed rent will consist of housing costs and housing benefits. Housing costs include mortgage payments or rent, whereas housing benefits include imputed rent (Frick et al., 2007). Although an owner occupier may not be paying rent or a mortgage, by living in the house they derive a benefit through this consumption (Mayer and Simons, 1994). Other benefits from being an owner occupier include a reverse mortgage (Nakajima and Telyukova, 2014). At the end of a life cycle imputed rent is shown to decrease inequality (Törmälehto and Sauli, 2013). A spatial model approach to imputed rent has been limited due to a lack of spatial information in surveys (Balcázar et al., 2014). There are no known studies which examine imputed rent at the small area level and calculate the impact on the spatial distribution of welfare due to the lack of income data at a spatially disaggregated scale.

Individuals spend a significant amount of their time commuting, which in most cases is considered an unpleasant (Stutzer and Frey, 2008), but a necessary activity. Automobile transport helps to reduce transport costs and enable people to live outside the high density centres (Glaeser and Kahn, 2004). This urban expansion and sprawl can lead to market failures such as congestion and a waste of resources spent on commuting (Wheaton, 1998). This inefficient allocation, results in workers travelling large distances to their place of work (Lyons and Chatterjee, 2008) and waste of resources (Van Ommeren and van der Straaten, 2008, Van Ommeren and Fosgerau, 2009). These commuting costs, both monetary and time, can be substantial (Rouwendal and van Ommeren, 2007). Commuting should be considered in the calculation of welfare.

Commuting is inextricably linked with housing, households may decide to locate to a residence further from work and have an increased commute in exchange for lower housing costs and larger amounts of living space (Glaeser and Kahn, 2004, De Bartolome and Ross, 2003). When this leads to excessive urban expansion, urban sprawl becomes an issue which can lead to congestion and high commuting costs, a trade-off exists between the gains from more space and the losses associated with urban sprawl (Brueckner, 2000). In these sprawl areas there is a greater reliance on the car and commutes tend to be longer compared to urban centres (Sultana and Weber, 2007). Commuting will therefore interact with both space and monetary income. An increase in income due to increasing living costs will increase the cost of commuting as the value of the time lost will also increase. This increase in the cost of commuting will disincentivise commuting, but at the same time the increasing demand and cost of space will encourage it (Becker, 1965). By including commuting costs in addition to income, the wage differential between urban and rural areas can be examined (Hazans, 2004).

One aspect of welfare which incorporates both housing and commuting elements, is access to local labour markets (Van Ommeren et al., 1999b, Dohmen, 2005). The spatial mismatch hypothesis (Kain, 1992), was used to explain high rates of unemployment among African Americans, largely due to geographical barriers to access concentrated job markets. Commuting distance to job opportunities will impact on the spatial distribution of employment (Rogers, 1997). Workers can be sorted in both the skill space and geographical space in a similar fashion (Brueckner et al., 2002). Low access and low availability of high skilled jobs can lead to a “low-skill, bad-job trap”, where there is a low incentive for workers to upskill and for firms to offer high skill jobs (Snower, 1994). High wages tend to be found where high skill workers concentrate in dense local labour markets (Combes et al., 2008). These thick labour markets will increase efficiency in matching worker skills to jobs (Krugman, 1998). Owner occupier, high skilled workers are more likely to move to find employment as the income they forgo when unemployed exceeds unemployment benefits and moving or commuting costs. Higher moving costs and lower mobility can raise unemployment (Dohmen, 2005). Those who are home owners are less likely to move residence for work, while job mobility is found to increase with commuting distance (Van Ommeren et al., 1999b).

Workers in rural areas are more likely to have greater commute times and likely to be net senders of workers to urban areas (Hazans, 2004). These local labour markets will have an impact on the economic viability of farming. A large percentage of farmers engage in off-farm employment (Kinsella et al., 2000). Due to the high reliance of agriculture on off-farm employment and subsidies (O'Donoghue, 2013), economically viable farming is influenced by spatial environment attributes and local labour markets. These spatial environment attributes, such as soil quality will impact on farm productivity with areas having distinct advantages (Frawley and Commins, 1996). As farming assets are largely immobile, farmers cannot simply move to have greater access to local labour markets. Spatial access to labour markets will therefore influence farm viability through a farmer's ability to find off-farm employment. The farmer's skill level is also likely to influence their probability of finding employment.

Welfare however can consist of other non-monetary aspects such as an individual's well-being, happiness or life-satisfaction (Frey and Stutzer, 2002). Socio-economic characteristics can have different effects on happiness (Ballas and Tranmer, 2008). Happiness has been found to be "u-shaped" with age (Blanchflower and Oswald, 2008, Clark et al., 1996). Space can impact on happiness via reference groups, people tend to be happier living in or close to rich neighbourhoods compared to poor ones (Firebaugh and Schroeder, 2009). The relationship between income and happiness is relative (Easterlin, 1974, Easterlin, 1995, Layard, 2011). Similarly the impact of unemployment on well-being depends upon the underlying unemployment rate of the area (Clark and Oswald, 1994). In addition to socio-economic and demographic drivers of happiness, happiness also varies across space (Glaeser et al., 2016). Individuals may derive welfare from local amenities, such as a scenic landscape (MacKerron and Mourato, 2013), facilities or the crime rate (Roback, 1982). Given the impact of local amenities on happiness (Brereton et al., 2008), the spatial distribution of happiness could be compared with the spatial distribution of income. This would highlight the importance individuals put on place and location.

Defining welfare is almost always a complex process. A number of approaches may be taken to measure individual well-being or welfare. When welfare is mentioned, the most widely understood definition is that of social welfare provided through the welfare state (Barr, 1998). This provides a minimum level of well-being to individuals through support mechanisms. Others use health as a proxy for welfare or use deprivation and poverty measures as proxies for welfare (Haase and Foley, 2009). Sen's capability approach measures individual welfare based on individual ability to conduct everyday tasks (Kuklys, 2005). The definition of welfare used here is an economic definition of welfare. Welfare is measured using a utility function which is calculated through individual revealed preferences.

Welfare can comprise of both monetary and non-monetary components. The Stiglitz-Sen-Fitoussi Commission (2009a) highlighted the need for a broadening of income measures to include non-market measures. Welfare can be defined using other non-monetary aspects such as housing (Frick and Grabka, 2003), commuting (Rouwendal and van Ommeren, 2007) and life satisfaction (Brereton et al., 2008). Adopting a methodological approach which includes spatial, monetary and non-monetary aspects of welfare will lead to in-depth analysis of welfare (UN, 2011). Various monetary and non-monetary measures can be used as proxies in an attempt to measure welfare and the variation that exists across space. This area of research is currently under studied in the Republic of Ireland (Ireland from here on) owing to a lack of detailed welfare data at a small spatial scale, or a lack of welfare data with detailed spatial information. This thesis combines spatial analysis with welfare data so that welfare can be examined across space at a small spatial scale.

Spatial Microsimulation

To overcome a lack of income data at a detailed spatial scale a spatial microsimulation approach can be used. Spatial microsimulation is a method which can aid in providing data on incomes at a detailed spatial scale, in this case at the individual and/or household level. As noted previously, spatial microsimulation works by matching survey data which contains information on incomes with Census data using common overlapping variables and calibrating the resulting dataset to published census population totals so that the data conforms to what is observed. A spatial microsimulation methodology has been used to examine many difference aspects of society including;

Poverty & inequality (Panori et al., 2016, Ballas, 2004, Ballas and Clarke, 2001, Harding et al., 2006, Miranti et al., 2011, Tanton et al., 2007, Tanton et al., 2009); income & wealth (Caldwell et al., 1998, Anderson, 2007, Ballas et al., 2014); health (Morrissey et al., 2008, Campbell and Ballas, 2016, Ballas et al., 2006a, Kosar and Tomintz, 2014, Smith et al., 2011, Morrissey et al., 2016, Morrissey et al., 2010); environment (Hynes et al., 2009b, Hynes et al., 2008, Ballas et al., 2006b); commuting (Lovelace et al., 2014), policy implications (Ballas et al., 2005a, Ballas et al., 2007) and education (Kavroudakis et al., 2013) among others.

What is clear is the potential for detailed spatial analysis when a spatial microsimulation approach is taken. This thesis will examine poverty and inequality in a spatial context. Intertemporal inequality is also examined while many of the recommendations outlined in Birkin and Clarke (1988) are added to the existing SMILE model which already contains income and a tax benefit model. Housing and commuting information are added to the dataset. We also consider spatial attributes of an area and their effect on happiness and general well-being. Geography and happiness has been combined and examined in several studies to examine happiness or quality of life at a small spatial scale (Ballas and Tranmer, 2011, Ballas and Dorling, 2013, Brereton et al., 2008, Tesfazghi et al., 2010). This literature is added to by examining welfare at a detailed spatial scale of analysis, namely the Electoral Division (ED) level.

This thesis benefits from the output of a spatial microsimulation approach. This allows us to examine the spatial distribution of welfare. Introducing distance into the estimation of welfare allows for different levels of commuting, housing costs and environmental attributes. Differences across space will also give rise to spatial inequality which can be measured both between and within area. Space also introduces non-monetary aspects of place into the measurement of welfare.

Spatial Distribution of Welfare

Clustering, congestion and associated externalities can suggest that outcomes are inefficient (Kanbur and Venables, 2003). Policy intervention is required to allocate resources efficiently where the market fails. High priced city centre parking and tolls are two measures used to combat the issue of congestion. Other externalities associated with clustering are spatial spill overs such as knowledge, industry and growth (Capello, 2009). Spatial spill overs however may stop at national borders and national macroeconomic factors will be a greater determinant on regional growth (Paas and Schlitte, 2006). Within countries regional income convergence is impacted by spatial autocorrelation. State income convergence will depend upon their regional neighbours (Rey and Montouri, 1999). Over the course of a countries life-cycle, regional inequality will follow a bell-shaped curve (Williamson, 1965). Authors such as Kakwani (1977) and Reynolds and Smolensky (1977) have put forward methods for the decomposition of policy interventions and changes in inequality. These methods add to the Theil index of inequality and allow policy interventions to be accessed as to whether they are progressive or regressive towards the income distribution.

In attempting to measure between and within area welfare an entropy measure is typically used (OECD, 2016a). Balisacan and Fuwa (2004) found spatial inequality accounts for a sizeable portion of national level inequality. More variation can be explained within-group rather than between; the within component dominates. Approximately one third of the variation however still occurs between-group which may be more cost-effective to address (Kanbur and Venables, 2003). Duro (2004) found a similar result in an examination of cross EU inequality, with 80% of the variation in spatial inequality being explained within rather than between using the Theil index of inequality.

Given that a lot of the variation will occur within rather than between regions, these issues will require a spatially disaggregated approach. Inequality can be measured in a variety of ways. Graphically using the Lorenz Curve (Lorenz, 1905) from which the Gini coefficient (Gini, 1912) can be derived (ratio of the area between line of perfect equality and Lorenz curve and the area between the line of perfect equality and line of perfect inequality). Inequality can also be decomposed into between and within group inequality using an entropy measure (Bourguignon, 1979, Shorrocks, 1980, Shorrocks, 1982). Typically, equivalised household disposable income is used in calculating these measures to account for household composition. Some measures of income however are not included in household income which can impact on an individuals' welfare such as in-kind benefits (UN, 2011), commuting costs (Roberto, 2008) and life satisfaction (Easterlin, 1995). This thesis contributes to the literature by including these measures into the measurement of welfare and examines them in a spatial context.

This thesis goes some way towards trying to understand these concepts such as interregional differences in welfare. A broader measure of welfare is adopted to encompass more than just income. This thesis attempts to understand these concepts in Ireland, by developing and applying methods to existing and new spatial data. This process will create a spatially rich welfare dataset which includes information on income, housing, commuting, labour markets and local environmental characteristics in addition to socio-economic and demographic characteristics typically reported in Census data. Measuring welfare is complicated; location, characteristics of the individual and the household, wealth, time will all interact with each other to determine an individual's, household's or area's overall welfare (Bourguignon et al., 2005). This thesis uses a number of methodologies in an attempt to calculate a comprehensive measure of welfare.

1.2 Contextual Framework

The measurement of welfare is important for policy. To access the impact of a policy the consequences on welfare can be far reaching. Policy can impact directly on welfare through taxes on earnings and consumption. Related to taxes are social transfers which attempt to reduce overall inequality through redistribution of resources. In a spatial context you have planning and rural development policies which influence numerous aspects of everyday life. They can determine how much time we spend commuting or our potential of finding employment.

Welfare Indicators

Department of Social Protection policy documents such as the "National Social Target for Poverty Reduction" (DSP, 2012a) and the "National Action Plan on Inclusion" (DSP, 2016) are aimed towards reducing poverty and inequality and improving social inclusion. Indicators of poverty such as at-risk of poverty measures based on equivalised household income, other material deprivation indicators and consistent poverty measures are used (Watson and Maître, 2012). The "National Action Plan on Inclusion" has a number of goals including:

- Ensuring children reach their true potential
- Supporting working age people and people with disabilities, to increase employment and participation
- Enabling older people to maintain a comfortable standard of living

- Improving the lives of people living in disadvantaged areas and vulnerable groups

The report however notes the particularly weak connection between cross-departmental policy and goals particularly in relation to education and employment (DSP, 2012b).

The think-tank for action on social change (TASC) outlines the use of 18 indicators of economic inequality in Ireland (Hearne and McMahon, 2016), including measures on income, employment, wealth and minimum wage. It shows that the top 10% own over 50% of the wealth. It believes the balancing of incomes is essential. A living wage, quality jobs and greater support for lone and low income parents who decide to take up work is required. The living wage provides workers with enough income to meet an acceptable living standard and be able to afford life essentials (TASC, 2016). The report also highlights where it believes the State is failing in its obligations towards children in the areas of child health, poverty and homelessness to name a few.

The Nevin Economic Research Institute (NERI) has examined changes in living standards and the income distribution as a result of a change in policy. Using income indicators such as at-risk of poverty and the distributional impacts of various taxes and benefits, it is possible to show the impact of policy changes on the income distribution and how the various decile groups are affected (Collins, 2014). Focus is also given to the incidence of low-pay in Ireland and how it varies depending on socio-demographic characteristics such as education, gender, age, industry and occupation (Collins, 2015).

Watson et al. (2017) used various Quality of Life (QoL) indicators to illustrate the multidimensionality of poverty. Indicators such as income poverty, deprivation, crowding and lack of social support were used to measure QoL problems.

Microsimulation models are used by policy makers for welfare analysis. The Economic and Social Research Institute's (ESRI) SWITCH model is a static micro-simulation model created using EU-SILC survey data. This survey data is grossed up to provide information on incomes, taxes and benefits (Callan et al., 2009). Currently ex-post budget assessment is carried out by the Departments of Finance, Public Expenditure and Reform and Social Protection and also externally by the ESRI, using the SWITCH model (Lawless and Reilly, 2016). The SWITCH model can be used to access the progressivity of tax measures. EUROMOD is a European wide static micro-simulation model. Similar to SWITCH, EUROMOD also uses EU-SILC data. Estimates are validated against external totals at both the micro and macro level to ensure accuracy (Sutherland and Figari, 2013, O'Donoghue, 2017).

Taxing Welfare

Policy can impact directly on individual welfare. Focusing on monetary income, the tax-benefit system that exists within the economy will determine disposable income. When you work to earn a wage, you pay a percentage in tax based on threshold value bands. Some of this tax received by the State is then re-distributed among lower income groups in an attempt to reduce inequality.

In an Irish context the tax benefit system reduces inequality. In 2014 the Gini coefficient of market income prior to taxes and transfers was 0.549, while the Gini of disposable income after taxes and transfers was 0.298 (reduction of 0.251) (OECD, 2017) (in comparison to Denmark 0.44→0.26 (0.18); Germany 0.5→0.29 (0.21); Sweden 0.43→0.27 (0.16); UK 0.52→0.36(0.16)). In addition to income tax there is a tax on consumption, value added tax (VAT), however the consumption we derive from consumer durables very often remains untaxed. This consumption tax is widely considered as being regressive (Kakwani, 1977). As a result of indirect taxes such as VAT, the bottom decile pay the highest proportion of income in tax in Ireland (Collins, 2014).

The housing sector is one asset most widely taxed by policy makers. In an Irish context the Income Tax Act 1967 taxed income from the letting of a property or the imputed rent to the owner occupier. This tax was later abolished in 1969. A domestic rates system had been in place in Ireland since the mid-19th century. These rates were used to fund local government and were based on the valuation of the property. The amount however was dependent on the level of funding the local government required for its annual budget. The system was abolished in 1978 amid political controversy (Daly et al., 2009). There had been much criticism of the bias surrounding owner occupation in Ireland (OECD, 2006) with recommendations for the introduction of a property tax (Daly et al., 2009). In 2013 a local property tax (LPT) was introduced (Walsh, 2013). The LPT is a self-assessed tax and it is the responsibility of the owner to select the correct band in which they believe their property belongs to. The LPT website contains some guidance in relation to this; however the bands are quite wide with little information given in relation to housing characteristics. This tax can capture some of the in-kind benefits from owner occupation, however as the tax is on all residential properties those renting privately and those with a mortgage are also impacted. Callan et al. (2010) recommended an income exemption were a property tax introduced however the current tax does not discriminate based on income or ability to pay.

Spatial Policy

The spatial distribution of welfare is influenced by a number of regional development and economic policies. Cities within the OECD are growing fast, by 2050 70% of the world's population will live in cities (OECD, 2015). As of 2016 within the OECD, 50% of the total population live in cities (OECD, 2016a) whereas 25% live in rural areas which make up 75% of the land (OECD, 2016d). It is however too simplistic to classify an area as urban or rural as the definition is not binary. There is a growing need to redefine what we mean by rural. Rural varies between areas that are close to urban areas which are more resilient; compared to remote rural areas which are vulnerable to economic conditions. The Rural policy 3.0 (OECD, 2016d) policy framework moves beyond farming and subsidising specific sectors towards making rural areas more competitive, adopting a community based approach. This new approach also recognises the different types of rural areas and recognises the opportunities that exist in rural areas outside of the agriculture industry. Teljeur and Kelly (2008) account for this spatial heterogeneity in a six-point urban-rural classification system based on accessibility and remoteness. Rural areas with a higher quality of life but lower wages can attract and hold onto workers and their families (OECD, 2016a). The use of spatial analysis can identify the causes and solutions for a range of issues such as inequality, segregation and life satisfaction.

Irish Context

The research in this thesis covers the turbulent economic climate 1996 – 2011. Over this period of fifteen years Ireland witnessed big changes in its economy. The "Celtic Tiger" period (1996-2000) saw large FDI led growth. The property boom-bust period (2002-2008) witnessed enormous expansion of the construction industry and subsequent bust as a result of a credit bubble and global financial crisis. Then finally the "Great Recession" (2008-2013) in which there were large numbers of unemployed and austerity measures were introduced to reduce government spending. It is important to understand how welfare changed over this period and how it is expected to change in the future.

In an Irish context, the examination of welfare in a spatial context has been hampered by a lack of data, particularly income data at a spatially disaggregated scale. Nolan et al. (1998) used 1987 and 1994 survey data to examine spatial poverty. They found poverty risk in small towns and villages to be the highest out of all urban-rural classifications. Housing tenure was found to be an important determining factor in the risk of poverty compared to location. Watson (2005) examined poverty at a spatial scale however were unable to carry out their analysis at a spatially disaggregated scale and were limited to a county level. They found spatial poverty to be diffuse. Similar findings to Nolan et al. (1998) countryside and rural areas being at particular risk to poverty and housing tenure being an important determinant. In all analyses, it was found that spatial variability in poverty was modest and took place within rather than between areas (O'Donoghue et al., 2013b).

Over the past fifty years the Irish government has introduced a number of regional planning strategies, some having more success than others. The Wright Plan (Wright, 1967) focused on the expanding city of Dublin and the issues around the dilapidating dwellings. It suggested the building of new towns in the suburbs around the city. Areas such as Blanchardstown, Tallaght and Ballymun were developed. As the people moved out however their jobs remained in the city. A lack of services and amenities in the new towns lead to social problems. The infamous Ballymun high-rise flats being one the legacies of this plan. The Buchanan Report (Buchanan, 1968) was commissioned to help in achieving more regional balance outside of Dublin. It set out the selection of national growth centres, regional growth centres and local growth centres where industry and growth could be concentrated. It was highly controversial however and failed to gain political support. The National Anti-Poverty Strategy (NAPS, 1997) put poverty and social exclusion near the top of the governments agenda. It was aimed towards tackling poverty with specific guidelines on how concentrations and pockets of poverty and deprivation can be combatted. It had a spatial dimension in two of its five main themes, highlighting the need for area based approaches.

The National Spatial Strategy (NSS, 2002) was a key document aimed towards more balanced regional development. Similar to the Buchanan Report it identified a number of gateways and hubs on which development and investment could be focused. There was however disagreement over this selection process with some viewing it as a winners versus losers type scenario (Daly and Kitchin, 2013). There was a lack of political commitment to the strategy and it had no legislative power. Policymakers and planners therefore viewed it merely as recommendations (Meredith and Van Egeraat, 2013). The National Development Plan (NDP) launched in 1988, set out a plan for the spending of Government investment typically over a seven-year period. For NDP 2006-2013 there was a budget of over €184 billion (NDP, 2000) available for investment in the areas of infrastructure, enterprise, science and innovation, social capital and inclusion and human capital. This investment is targeted towards the gateways from the NSS to promote more regional balance. Unlike its predecessor the NDP 2000-2006 (NDP, 2000) which was at a coarse spatial scale, NUTS 2 region level of which there are only two (Border, Midland, Western Region and South Eastern Region), the NDP 2006-2013 was more spatially refined.

Concern around the increasing divergence between urban and rural areas; lead to the Commission for the Economic Development of Rural Areas (CEDRA) report being commissioned (CEDRA, 2014). CEDRA detailed specific recommendations on how to improve rural areas and increase development. On the recommendation of the report, a Senior Ministry for Rural (and Community) Development was established in 2017 and an action plan for rural development created (Rural Ireland, 2017). The action plan outlines actions points grouped into pillars, with the overall aim of improving opportunities, skills and economic growth in rural areas. Other recommendations from the CEDRA report which were acted upon were the Town and Village Renewal Scheme, the Rural Economic Development Zone (REDZ) initiative and the creation of the Local Enterprise Office network (Rural Ireland, 2017). The REDZ zones are "*functional rather than administrative geographic areas that reflect the spatial patterns of local economic activities and development processes*" (CEDRA, 2014). The Town and Village Renewal Scheme is aimed at improving the liveability and spatial amenities in small towns and villages (Rural Ireland, 2017). These schemes have only recently been launched (DoCHG, 2017); it will be interesting to access what the impact of these schemes will be on the improvement of rural areas.

The latest spatial planning strategy is the National Planning Framework (NPF, 2017) which is due to be launched in 2017. The NPF is focused on creating a long-term plan for future needs of Ireland. A long-term plan is required so that the right development, takes place in the right areas at the right time. Unlike its previous the NSS, the NPF does not adopt a gateway and hub approach, instead adopting a more holistic view. The inclusion of themes on health and well-being, sustainability and climate change are welcome and show a focus not just on economic growth and development. Ireland faces increasing risk to climate change with wetter winters and drier summers expected (Sweeney et al., 2008).

It is striking that of the twenty-two fastest growing towns between 2002 and 2016, not one was a NSS gateway or hub. In terms of actual population growth, the level of growth in the twenty-two fastest growing towns and the growth in the twenty-two gateways and hubs was almost identical. The average population of these twenty-two fastest growing towns was 6,000 in 2016, while the average population of the gateways and hubs in 2002 was just under 30,000 people (NPF, 2017). It would seem people are choosing to live in smaller towns and villages and moving away from living in the major cities.

In Ireland a number of studies have examined welfare at a spatial scale. The development of a small area deprivation index for Ireland (Haase and Foley, 2009, Haase and Pratschke, 2012b) has gained a lot of attention and is now used in the calculation of the Residential Property Price Index (RPPI) (CSO, 2017) to measure the social advantage or disadvantage of an area. The index is calculated based on demographic, social class and labour indicators which gives each small area index scores with a mean of zero and standard deviation of ten (Haase and Pratschke, 2012a). Meredith and Faulkner (2014) examined the geography of the labour force in Ireland 1991-2011 but found little change in labour characteristics of areas over this period. Morgenroth (2010) used POWCAR 2006 data (Census travel to work data) to examine economic activity at the ED level, highlighting the difference in the spatial distribution of employment between sectors. Locational requirements of different sectors vary with some sectors favouring an urban environment. McCafferty (1999) examined the socially deprived areas of Southill in Limerick which rank in the bottom deciles of the national distribution. Sixteen of the forty-seven wards in Limerick City rank in the bottom decile, accounting for 40% of the city’s population. The blog Ireland after NAMA has some interesting spatial analysis of socio-economic trends. Gleeson (2009) highlighted that the areas which already had high numbers of unemployed, also had the biggest increase in the Live Register between August ’08 and February ’09.

O’Donoghue et al. (2013b) utilised a spatial microsimulation approach to match EU-SILC data with Census SAPS to examine market, gross and disposable income at the

ED level for the year 2002. O'Donoghue et al. (2013a) highlight the need for broader measures of welfare. So far only the spatial distribution of welfare for the year 2002 has been examined. Given the time period since has included the property boom-bust and great recession periods, a greater understanding of the local area socio-economic and demographic changes which occurred over this period is required. So far the measure of welfare used have been cash based (O’Donoghue et al., 2013b) however welfare encompasses more than just income. It recommends the inclusion of travel to work data to measure the welfare cost associated with commuting, including both direct and indirect costs of commuting (opportunity cost of time) as well as the importance of incorporating a measure of happiness, so that the local environmental characteristics are considered.

Motivation

The main motivation behind this thesis was to examine welfare, both monetary and non-monetary drivers in a spatial context. Considering welfare in a spatial context, accounts for the variability that exists between and within area. The issue with examining welfare spatially however is a lack of data. The census, which is spatially rich, contains no income data. Likewise survey data which has income data does not have a spatial component. Using the output from a spatial microsimulation model, helps in overcoming this issue. The final simulated population dataset contains individual, household and area unique identifiers. Attached to each individual is a set of socio-economic and socio-demographic variables such as age, employment status, housing tenure, income and education attainment. Using this synthetic dataset additional spatial drivers of welfare can be added to create a more comprehensive spatial distribution of welfare.

In an Irish context we will be able to identify spatially, the areas with the lowest levels of welfare. Each paper performs a sensitivity type analysis on welfare and examines the impact of that specific driver of welfare on the distribution. It will be possible to answer how welfare has changed over time, how commuting and housing is impacting on welfare, the impact of local labour markets on agriculture and how environmental characteristics affects the level of welfare in an area. By taking this approach the impact of the various welfare measures on the welfare distribution can be measured spatially. The affect the measure has on the overall level of inequality can be quantified. In measuring inequality there is growing attention paid to capital and nonwage income

(Piketty et al., 2014). This will give us a greater understanding of how wealth and income is distributed and any possibly measures which could be introduced to redistribute welfare in a more equitable way (Atkinson, 1983). The impact the drivers of welfare on the overall income distribution can be measured; the impact on those in the lower deciles versus those at the upper end of the distribution. By adopting this approach the distribution of welfare for each measure can be compared to the spatial distribution of disposable income (the base measure in this thesis).

Since starting the PhD in 2013 there have been increasing levels of technological progress (Moore, 1998). This has made it relatively inexpensive to store vast quantities of data in the "cloud". The consequences of this for researchers are new open source data portals and more information being stored online. Sources such as OpenStreetMap, Dublinked and Data.Gov.ie are invaluable resources. This data can be used and enhanced to answer the research question of interest to the researcher. In recent years such data was unavailable and collecting this data, especially spatially detailed data, was very time consuming. This recent advancement has great potential for further collaboration amongst researchers. The surge in the amount of big data available also presents further opportunities.

It will be the challenge of policy in the coming years to come up with policies which create high skilled jobs in rural areas and at the same time attract and retain talent in these areas. Given the increasing congestion city living is becoming less attractive. Policies aimed at taking the jobs out of the cities may go towards easing this congestion and easing pressure on infrastructure in these regions. One of the major challenges in rural areas is the provision of services which are more expensive to provide on a per capita basis compared to urban areas, due to their scattered nature (OECD, 2016b).

This thesis benefits from building upon a collaborative model which has enabled small area estimates of income be calculated. Efforts to estimate welfare at a spatial scale are often restricted by a lack of data of this kind. This area of research has not been ignored but rather it has been restricted by a lack of income data at a spatial scale.

This thesis builds on the work of O'Donoghue et al. (2013a) by updating and adding to the SMILE model. This includes examining welfare over time and using a broader definition of welfare so that it includes more than just income. Commuting costs will be calculated so that the impact of commuting on the spatial distribution of welfare can be examined. You would expect those living in the suburbs around the major cities to have a longer commute compared to those in the city. How do these costs vary across space and what impact do they have on the income distribution and inequality? In addition to commuting, housing costs are also added. Small area estimations of property rents and values are generated using spatial econometric techniques. The impact of local labour markets on the viability of rural areas is investigated. A measure of self-reported life-satisfaction is added. This life-satisfaction data is linked to spatial attributes so welfare can be linked to local characteristics. Finally, the methodologies developed in this thesis are applied to a case study which examines the in-direct costs of a flooding event as well as the spatial distributional impacts. This highlights how the methodologies used in this thesis can be applied in a policy scenario.

1.3 Thesis Objectives

This thesis aims to examine welfare using a broader definition of welfare which includes more than just disposable income. Other monetary and in-direct costs and benefits are included into the calculation of welfare. Non-monetary income is also included. The sensitivity of these drivers of welfare is examined at a detailed spatial scale. Spatial methodological approaches enable the issue of a lack of data at a detailed spatial scale to be overcome.

A number of interesting questions are answered and a number of gaps in the existing literature are filled. Current studies examining small area estimations of welfare have been hampered by the previously mentioned lack of welfare data at a detailed spatial scale. Typically studies focusing on income are at an aspatial scale. The data typically comes from surveys and tends not to have a spatial component. The output from a spatial microsimulation approach is used to overcome some of the issues faced in previous studies such as a lack of spatial income data. Spatial microsimulation is a method which links census data with survey data to create a new synthetic population dataset which has both a spatial component and as well as detailed socio-economic and demographic information, including income.

This thesis seeks to address these issues by developing different measures of welfare using various definitions and examining the sensitivity of each measure on the spatial distribution of welfare. Time, space, housing, happiness derived from the spatial attributes are all examined. Income, more specifically disposable income, is used as the baseline measure of welfare and monetary and non-monetary components and drivers of welfare are then interacted to obtain a new spatial measure of welfare. Using this simulated dataset will allow us to test the impact of spatial drivers on the distribution of welfare. These include:

- Income derived from in-kind benefits in the form of consumption derived from consumer durables
- The effect of location on commuting and leisure times
- The impact of local labour markets on the economic viability of farming
- Levels of income derived from spatial attributes and how this compares to when disposable income is only considered
- A case study using the methodologies developed to access the indirect welfare costs of a flooding event

Each of the drivers of welfare will involve the use of spatial analysis to calculate small area measures of the component in question. Housing is calculated at a small spatial scale using kriging, commuting costs are generated adopting an OD cost matrix method and income from spatial attributes are derived using a parametric match.

The main contribution of this thesis is the bringing together of monetary and non-monetary aspects of welfare with space. Each paper examines the impact of a different welfare component on the distribution and all analysis is conducted at a disaggregated spatial scale. Using this approach allows the intricacies of the impact each component has on welfare be assessed. The components examined cover a broad range of areas such as income, time, housing, commuting, agriculture, geography and happiness. In total, there are five six papers each contributing in a significant way to the literature:

- A spatial distribution of disposable income is calculated over time. An intertemporal examination of small area income such as this has not been done before.
- Housing costs and benefits are estimated at a small area level and their impact on household income is measured. Previous studies of imputed rent using spatial models have been hampered by a lack of spatial information in survey data.

- Commuting costs are included in the calculation of welfare. The impact of these costs on a commuter work income is examined.

- The impact of local labour markets on the viability of farming is assessed. This paper shows how the physical and structural differences between areas can interact with each other.

- Welfare is broadened even further to include the impact of local environmental characteristics on an individual's life-satisfaction and how this distribution differs greatly to that when just income is considered.

- Some of the methodologies employed are utilised in a case study which focuses on the indirect costs to commuters as a result of a flooding event. Understand the costs of such flooding events are of greater importance given the increased risk due to climate change.

The objective is to examine the levels of welfare at a small area level. Being able to measure welfare in such detail will allow for trends and areas of affluence or poverty be identified. Observing welfare at an individual and household level will allow comparisons between different demographic groups and different socio-economic groups. Each paper examines a different aspect of welfare. Taking this approach makes it possible to assess the impact each additional instrument has on welfare. By observing the trends across area and group it is possible to separate who the additional welfare measure benefits and who it costs. Taking each instrument separately ensures we are able to capture these effects.

1.4 Structure of Thesis

The aim of this thesis is to examine the relationship between space (spatial area) and welfare (monetary and non-monetary). Previous studies have been hampered by a lack of data of a spatial scale. These issues are overcome through a combination of microsimulation, spatial analysis and GIS (geographic information system) techniques. Using the data output from SMILE, spatial distributions of welfare are created with each spatial distribution adopting a different definition of welfare. This enables the sensitivity of the distribution to the change in welfare definition to be examined.

A spatial distribution of welfare will be calculated using:

1) Intertemporal disposable income 1996-2011

2) A housing component consisting of imputed rent and housing costs

3) Commute times and travel costs (monetary and time costs)

4) Impact of local labour market on farming viability

5) Non-monetary welfare (life-satisfaction) derived from spatial attributes

6) Indirect welfare costs due to an extreme weather event

For this thesis six spatial distribution maps of welfare will be created. These spatial distribution maps will be constructed using various census data, survey data, along with other spatial data collected. These maps will show that there is a spatial element to welfare that is largely ignored. Each spatial distribution map in this thesis will be produced using GIS software and will show each of the 3,400+ Electoral Divisions (ED) using colour coding to indicate the level of welfare. Maps are the most efficient and effective way of displaying spatial data. The distribution maps created will allow for any spatial pockets of welfare deprivation that may exist in Ireland to be clearly identified.

Brief summary of each chapter

Chapter 2

This chapter focuses on the methodologies employed. The spatial microsimulation model SMILE is introduced and the steps involved in creating a synthetic population representative dataset are outlined. It describes how the SMILE model has been updated and enhanced in this thesis by the addition of monetary and non-monetary drivers of welfare. Spatial analysis techniques and methods around the creation of these drivers and measures are explained in greater detail. Spatial methods are required to create spatially refined data not currently available.

Chapter 3

Welfare is examined for four census years; 1996, 2002, 2006 and 2011. Using spatial microsimulation and spatial methods, a spatially rich dataset for each year is created. This dataset is then used to create a spatial distribution of disposable income. Disposable income is equivalised to account for household composition. Dividing the income distribution into quintiles, and weighting each quintile by the population of the district, allows for changes to be tracked effectively over time and to analyse the movers. In addition to the welfare measure, the characteristics of these areas are used to measure progress. Measures such as old age dependency, youth dependency, unemployment rate and tertiary education rate give us a good idea about the type of areas which have moved up or down a quintile over time. In this chapter both space and time are considered. By adopting this approach we can examine if there are clear disparities between different areas of the country. The Celtic Tiger, Property Bubble and Great Recession will all impact on different regions in different ways.

Paper Outputs:

Paul Kilgarriff, Cathal O'Donoghue, Martin Charlton, Ronan Foley (2016). "Intertemporal Income in Ireland (1996-2011) – A Spatial Analysis". International Journal of Microsimulation (IJM), 9(2), 123-143.

Chapter 4

This chapter examines the impact of housing on the spatial distribution of welfare. Again the spatial distribution of disposable income provided by SMILE forms the base measure of welfare. To this base measure we calculate housing costs and benefits for each household. The first task in this paper is to calculate rental values spatially. The kriging methodology is used to interpolate rental and property values. Kriging has the benefit of presenting the error term which is attached to each estimated rental value. Property value data used originates from the Daft.ie report and Department of the Environment data. The spatial impact of net imputed rent, mortgage payments, private rent, public rent (social housing schemes) and annuity values on the distribution of disposable income from SMILE for the year 2011 is then examined. 2011 is the focus of this chapter, as it is the latest Census year for which detailed spatial micro data is available. Measuring the impact of housing on welfare spatially, accounts for the differences in property values across space. Using household level data considers the socio-demographic and economic differences that exist such as life-cycle impacts. This analysis can inform policymakers of the groups which experience the largest decrease in welfare as a result of housing both within and between areas. Conducting this analysis spatially allows for these important spatial differences that exist in housing such as the variation in house price across space.

Paper Outputs (Planned):

*The aim is to prepare this paper for submission to the journal “Review of Income and Wealth”

Presentation Outputs:

Oct 27th 2016 - RSA Student and Early Career Conference, Northumbria University, Newcastle. Title: “Effect of Housing on the Spatial Distribution of Welfare – A local level imputed rent measure for Ireland”

Sept. 4th, 2015 – International Meeting of the International Microsimulation Association, Esch-sur-Azette, Luxembourg. Title: “Effect of Housing on the Spatial Distribution of Disposable Income”

Chapter 5

This chapter examines the spatial impact of commuting on work income. As the population of our urban areas increase, there is more competition for a limited supply of land. This in turn pushes workers out into the suburbs and commuter zones. Some of these individual’s commute long distances each day which costs both in terms of fuel and running costs but also the opportunity cost of the time spent commuting. A methodology is introduced which measures an OD cost matrix for journey times and distances. This information is linked to the CSO’s Place of Work, School or College, Census of Anonymised Records (POWSCAR) data which in turn is linked to individual SMILE data to produce a geo-referenced, attribute rich dataset containing commuting, income, demographic and socio-economic data. This enables the impact and effect of commuting on the spatial distribution of income be assessed. The areas facing the highest commuting costs can be identified and the characteristics of these areas summarised.

The main writing of this paper and calculation of the value of time values were carried out by the first author, the spatial analysis including the calculation of commuting costs, OD cost matrix and mapping were conducted by the thesis author.

Paper Outputs:

Amaya Vega, Paul Kilgarriff, Cathal O'Donoghue, Karyn Morrissey (2016). "The Spatial Impact of Commuting on Employment Income - A Spatial Microsimulation

Approach" - Applied Spatial Analysis and Policy, Springer. DOI: 10.1007/s12061-016-9202-6

Presentation Outputs:

May 6th, 2016 – Irish Economics Association Annual Conference, NUI Galway. Title: “The Spatial Impact of Commuting on Employment Income”.

Feb. 3rd, 2016 – Brown Bag Seminar, Department of Economics, NUI Galway. Title: “The Spatial Impact of Commuting on Employment Income” - presented on the effect of travel costs on personal income.

Chapter 6

This chapter focuses on the impact of local labour markets on the spatial viability of agriculture. A viability classification concept is utilised to classify a farm’s economic viability as viable, sustainable or vulnerable. A spatial microsimulation approach is used to add a spatial component to a farm micro dataset. This dataset is then linked to a spatial micro dataset of households which allows for farm and non-farm analyses within the same analysis. The percentage of farms in an area belonging to each classification is calculated at the ED level. This dataset enables us to analyse the characteristics of the areas at a detailed spatial scale. This chapter aims to show that spatial differences in viability exist and how access to local labour markets is one of the main drivers. There is significant heterogeneity in employment, types of employment and access to labour markets. The results show how the different viability measures are concentrated to a particular area.

The methodology section of this chapter is adapted from a supervisor’s previous work O’Donoghue (2013).

Paper Outputs (Planned):

*The aim is to prepare this paper for submission to the journal “Irish Geography”

Presentation Outputs:

Oct 23rd, 2015 - European Association of Agricultural Economists, Edinburgh, Scotland. Title: “Farm Viability: A Spatial Analysis”.

Chapter 7

In this chapter the impact of the local characteristics of an area on welfare is examined spatially. This chapter is the first time a measure of welfare calculated using non-monetary income is introduced. There are other spatial attributes of the environment from which individuals can derive utility. Utilising the results of a self-reported life-satisfaction study a parametric match is performed to estimate life-satisfaction at the ED level. This distribution of welfare is compared with that when just income is considered. By adopting this approach the unique attributes of area are considered. When we introduce the importance of place the value of the spatial attributes is introduced into the measurement of welfare. By analysing the quintiles, EDs which move up or down the welfare distribution are identified. The characteristics of these areas both socio-demographic and socio-economic but also the spatial attributes are summarised. Contrasts may exist between areas which are income rich but welfare poor.

Paper Outputs (Planned):

*The aim is to prepare this paper for submission to the journal “Ecological Economics”

Presentation Outputs:

Oct 23rd, 2014 - European Meeting of the International Microsimulation Association, Maastricht, Netherlands. Title: “Quantifying the Impact of Space on the Distribution of Welfare”.

Chapter 8

This empirical chapter illustrates how some of the methodologies outlined in this thesis can be used in applied policy analysis. An OD cost matrix is estimated, similar to chapter 5. Unlike chapter 5, this OD cost matrix is estimated taking into account an extreme weather event which severely flooded roads resulting in their closure or severely reducing speed. This OD cost matrix is re-estimated several times to account for changing status of road segments. Very often when the costs of a disaster, such as a flooding event are being measured; only the direct costs are measured. The indirect costs are often ignored due to their difficulty of measurement. The indirect costs to commuters, both the extra distance travelled and the extra time cost are measured. The impact of this extra cost on work income is measured across income groups. The groups most disproportionately affected by the flooding are identified and the characteristics of the areas summarised.

Presentation Outputs:

May 5th 2017 - Irish Economics Association Annual Conference, Institute of Banking, IFSC, Dublin. Title: “Counting the cost of last winter’s flooding: Evidence from disruptions to the road network”.

Oct 28th 2016 - RSA Student and Early Career Conference, Northumbria University, Newcastle. Title: “Effect of a Flood Event on the Daily Commute”

*This work has been presented to policy makers from the Department of Climate Change, EPA and Office of Public Works.

Paper Outputs (Planned):

*The aim is to prepare this paper for submission to the journal “Applied Spatial Analysis and Policy”

1.5 Thesis Contribution

The content of this thesis comprises of elements from three disciplines; economics, geography and geocomputation. This enables a multi-disciplinary approach to be taken on the distribution of welfare. This thesis adopts various methodological approaches from different disciplines to answer a number of questions not previously addressed.

This thesis is unique as it uses data not typically available in Census data. Typically Census data contains no income information but has a spatial component whereas survey data has information on incomes but has no spatial component. Spatial microsimulation is a method of linking the two datasets together to create a synthetic dataset containing income and other socio-economic and demographic data all at a detailed spatial scale. The data from SMILE presents a measure of income after taxes and benefits at an individual and household scale and is used to overcome the lack of spatially disaggregated income data. Using the SMILE dataset as a base, welfare is measured accounting for various definitions. Welfare is used in this thesis as a broad umbrella term. Disposable income is used as the base measure of welfare with other monetary and non-monetary sources of income such as time, space, housing, commuting, labour markets and happiness each added separately. This thesis has been able to take this previously created spatial distribution of disposable income and enhance the spatial distribution of welfare by examining different drivers of welfare in a spatial context.

The spatial distribution of welfare is examined across time, taking account of housing wealth, the cost of commuting, access to local labour markets and finally we compare the spatial pattern of disposable income with a pattern of happiness. Another unique aspect of this thesis is the creation of new micro, spatially disaggregated datasets using geocomputation techniques. Spatial disaggregated housing (rental and property prices), commuting (journey times and journey distances), farm viability, flood risk and happiness data (using a parametric match) are created and merged into the SMILE population dataset. These methodologies have a wide potential for further usage. This potential is highlighted in chapter 8 which utilises the methodologies to calculate the in-direct and distributional costs of a flooding event.

Chapter 3 examines welfare across both time and space. This is a significant contribution to the literature as such a study has not previously been done. Studies have examined welfare across time and welfare across space but not simultaneously. Disposable income is used as a proxy for welfare and examined across four census years. This is not panel data however so we are unable to follow individuals and households across time periods. We are however able to examine the characteristics of areas and how they have changed over time.

In chapter 4 the income derived from consumer durables such as housing is examined in a spatial context. This income takes the form of imputed rent, the benefit an owner occupier receives by not having to pay rent. Other costs and benefits of housing are also considered such as mortgage payments, private rent and reverse mortgage payments. Previous studies of imputed rent have been restricted to an aspatial scale due to a lack of income data with a spatial component (Balcázar et al., 2014). This study has been able to benefit from the output of spatial microsimulation to examine imputed rent at a small area level. Spatial housing information is added to the spatial distribution of disposable income from chapter 3. This spatial information on incomes has allowed us to use spatial methods such as kriging, to estimate rent and property prices at a detailed spatial scale and link these values back to individuals. It is clear from our estimates that there is significant heterogeneity around house prices which should be accounted for.

Chapter 5 again uses the spatial distribution of disposable income from chapter 3 however this time commuting information is added to the measure of welfare. Having individual specific travel times and distances makes it possible to estimate both the monetary and non-monetary costs of travel. Non-monetary costs are important to consider as commuting can impact negatively on leisure time available. This paper combines both spatial microsimulation and spatial network analysis to present a unique dataset for Ireland which examines the impact of commuting on employment income at the electoral division (ED) level for the first time. This newly created spatial distribution of income is then used to analyse the impact of commuting across space and also how it impacts on different income groups.

Chapter 6 builds upon the analysis conducted in O'Donoghue (2013) by examining the characteristics of areas by viability classification (Frawley and Commins, 1996). Whereas O'Donoghue (2013) looked at the impact of farm income and subsidies on the viability of farming, this chapter focuses on the impacts of local labour markets, spatial attributes and other characteristics on the spatial viability of farming. Getis-Ord Gi* is used to examine clusters of farm viability, sustainability and vulnerability. A cross-tabulation with unemployment is used to examine both areas of high unemployment and high farm vulnerability.

Chapter 7 takes what we have learned from the previous chapters on the impact of space on welfare but focuses on the non-monetary income drivers of spatial welfare. Individuals will derive non-monetary income from spatial attributes specific to an area. This chapter highlights the benefit of using a parametric match to add a spatial component to regression results. This chapter compares the differences between the spatial distribution of welfare when disposable income is used as a proxy to the spatial distribution of welfare when life-satisfaction is used as a proxy. This life-satisfaction is a function of the utility an individual derives from the spatial attributes of the area. This chapter differs from previous studies by examining the socio-economic and demographic characteristics of the areas at a spatially disaggregated level.

Chapter 8 is research which has been carried out as part of a broader project. Adopting similar methodologies and concepts outlined in this thesis have been applied to examine the in-direct impacts of climate change. This chapter is a case-study to illustrate how such methodologies can be applied in practice to influence policy making. This chapter focuses specifically on the costs and distributional impacts of a flooding event on commuters. This study is unique as it uses very detailed spatial information which is time stamped to access the costs at a very micro level.

This thesis has updated and created some new methodological approaches which can be used to examine spatial welfare. The spatial microsimulation model SMILE has been updated to examine a number of important drivers of spatial welfare.

1. The output from SMILE for four census years (1996, 2002, 2006 and 2011) has been examined in a spatial context. The characteristics of the areas which had increasing or decreasing levels of welfare over this period were examined. This paper highlights the importance of space in intertemporal analysis. Previous studies in this area have examined intertemporal welfare, or spatial welfare. This is the first study of its type which examines welfare across both time and space.

2. Housing information is linked to the SMILE dataset. This housing information is estimated at a detailed scale taking into account spatial differences in prices. The impact of imputed rent, private rent, mortgage payments and annuity payments on the spatial distribution of welfare can be measured. Previous studies focusing on imputed rent have been restricted due to a lack of income data with a detailed spatial component.

3. Journey distances and times for commuters were estimated using GIS software. Journey distances and times from census data can be unreliable as they are stated values. This commuting information is linked to the SMILE dataset. This allows us to assess the impact of commuting on employment income. Previous studies have been hampered by a lack of spatial employment income data.

4. The viability of farming is examined in a spatial context. Previous studies which examined farm income levels are extended to examine the spatial characteristics and spatial attributes of these areas. A farm classification system is used to group farms based on economic performance. The impact of local labour markets on the farming sector and rural areas in particular is the main contribution of this study.

5. This chapter compares the spatial distribution of disposable income to the spatial distribution of welfare. Results from a life-satisfaction survey are utilised through a parametric match methodology and used as a proxy for welfare. This

measure of welfare considers the spatial attributes of the area. This is the first study of its kind which compares disposable income and welfare in a detailed spatial context.

6. The final chapter is a case study which applies the methodologies developed in this thesis. Using the spatial distribution of income from SMILE the indirect costs of a flooding disruption are calculated. Spatial methods are used to estimate the added journey times and distances as a result of the disruption. With the increasing risk of climate change such events are more likely to occur. This study is the first of its type which measures the indirect costs of an extreme weather event and examines the impact on the spatial distribution of income.

These studies have made considerable contributions to the literature as evident through the dissemination of the various studies either in peer-reviewed journals, international conferences and national policy workshops.

Chapter 2. Data Methods and Models

Measuring both monetary and non-monetary aspects of welfare at a spatial scale will require detailed information at a spatially disaggregated scale. The issue however is the census, which is spatially rich but contains no income data. Likewise survey data which has income data does not have a spatial component. Using the output from a spatial microsimulation model helps us to overcome this issue. The final simulated population dataset contains individual, household and area unique identifiers. Attached to each individual is a set of socio-economic and socio-demographic variables such as age, employment status, housing tenure, income and education attainment. The base spatial distribution of welfare will use disposable income as a proxy.

The dataset produced using spatial microsimulation does not contain any detailed spatial information on levels of housing benefits or costs, commuting times, commuting costs, income from spatial attributes or others impacts of place such as local labour markets. Many of these components which should be included in a comprehensive measure of welfare face similar issues to disposable income such as a lack of spatial data. To overcome these issues spatial methods are applied to interpolate and estimate property prices, rental prices, commuting times, commuting distances, level of service provision, environmental attributes and life-satisfaction levels at a detailed spatial scale.

2.1 Spatial Microsimulation

Introduction

Currently there exists no spatial data that links both socio economic and demographic data with data on income, in order to overcome this problem we must utilise SMILE. The first methodological issue is this instance is in relation to the generation of a measure of disposable income. Disposable income is not included in a published source such as the small area population statistics (SAPS). In order to overcome this issue, it will therefore have to be generated using survey data. This thesis utilises the output of a previously created model, the simulated model of the Irish local economy (SMILE). SMILE is a spatial microsimulation model, which can assist in overcoming the problems associated with lack of data. The model uses a quota match method to populate a dataset with households this is followed by a calibration method which then assigns market incomes to these households while the tax-benefit microsimulation component of SMILE presents a measure of disposable income for each household.

SMILE helps in overcoming the problem of having a lack of data at a spatial scale. The dataset created by SMILE contains demographic, socio-economic, labour force and income variables at the micro-level for both individuals and family units (O'Donoghue et al., 2013a).

The output from a microsimulation model is being used in this thesis to overcome the lack of a spatially disaggregated dataset. The SMILE model will be utilised in order to obtain a spatially disaggregated measure of disposable income for each of the 3,400+ EDs in the Republic of Ireland. The Small Area Population Statistics (SAPS) contains useful data on the composition of households but does not contain any data on income (O'Donoghue et al., 2013b). Such a dataset would enable us to conduct analysis of households with their spatial locations (O'Donoghue et al., 2013a). Spatial microsimulation is a way of synthetically creating large-scale micro-datasets at various geographical scales (Morrissey and O'Donoghue, 2011). This chapter gives some more detail around how a measure of disposable income at a small spatial scale is estimated and describes the SMILE model which has generated the disposable income measure used in this thesis.

Model Construction

Spatial microsimulation can help in overcoming a lack of income data at a spatially disaggregated scale. SMILE utilises a data fusion process where micro data is matched using a statistical algorithm with census data to generate spatial micro data (O'Donoghue et al., 2013a). The objective of SMILE is to give spatially disaggregated data spatial attributes and in so doing add extra information to existing spatially disaggregated data.

The SMILE model uses a Quota Sampling (QS) methodology, developed by Farrell et al. (2010), that is based upon simulated annealing, which reweights survey data according to quotas for each area. It works by firstly randomly ordering the micro data, it then samples from the micro data until the quotas - which are set by the constraint variables from the census - are filled. The first version of SMILE (SMILE2002) was based on 2002 Census of Population data and the Living in Ireland Survey (2001) and used a combinational optimisation algorithm, simulated annealing (Morrissey et al., 2008). Although 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 the simulation (Farrell et al., 2013a, Hynes et al., 2009b). As a result, to create SMILE 2006 and match the Small Area Population Statistics (SAPS, 2006), SILC (2005) and POWCAR[2] (2006) datasets a more computationally efficient method known as quota sampling was developed by Farrell et al., (2013).

In the SMILE procedure, a limited number of constraint variables are chosen, this is due to computational efficiency and the non-convergence if a large number of variables are used. Regressing the main desired analytical variable, household disposable income, against potential match variables, an R^2 value is calculated. The three constraining variables used in SMILE are education level, age group and household size. These variables were used so that an accurate number of households per district are selected.

The first stage of the modelling procedure involves filling the quotas for the individual's most at risk of underrepresentation first. Demographic characteristics of those households at risk of being underrepresented in the model are identified. This allows for these households to be filled first with all constraints used. A random distribution of households sorted by household size is created. Using this ordering ensures an accurate number of households. This stage ends when no further households can be assigned. The next stage involves the creation of a demographic profile of those quotas unfilled. The next stage involves broadening the constraints. At this stage quotas have reached 95% accuracy. A constraint is removed after each iteration until the quotas are filled. The spatial microsimulation procedure is complete when a selection of individuals from the micro dataset can reproduce the SAPS tables with a less than 5% difference. The output file for each district contains the same number of individuals and households as in the SAPS, this ensures that it can be spatially aggregated and disaggregated by ED, county or province. The remaining variables in the microdata set are merged into the simulated data based on the common individual and household identifier.

Calibration

To test the reliability and credibility of the simulated data it is necessary of the model to be validated. This will involve in-sample validation, out-of-sample validation and multiple-module validation.

[2] The POWCAR was replaced by the POWSCAR for the 2011 census and includes extra travel to school and college data.

The in-sample validation involves comparing the proportion in each area by age group generated using our sampling mechanism and in the SAPS. In other words, the proportion generated using the simulated data is compared with the proportion generated using SAPS data. In this way, the simulated data is being scrutinised against published data. Such in-sample validation can be used as the variables, in this case age, overlapped between the two datasets.

Where data did not previously exist, out-of-sample validation is used. This method of validation involves comparing the synthetic data with new external data, with the data in both datasets aggregated to the same spatial scale. In the case of the SMILE model, at-risk of poverty estimates from Watson (2005). Poverty estimates from SMILE simulated data, are compared with estimates from external data.

One of the major issues with spatial microsimulation is in relation to the non-overlapping variables which are likely to suffer from unexplained spatial heterogeneity. As mentioned earlier the overlapping variables in SMILE are age, sex, education and number of persons per household. Non-overlapping or unconstrained variables include labour market variables such as occupation, employment status in addition to housing variables; have a mortgage, renting etc. An out-of-sample validation of the unconstrained variables against new external data highlighted substantial variability in the correlations amongst the unconstrained variables. A Monte-Carlo Simulation approach is adopted in SMILE to attempt in correcting some of these problems (O'Donoghue et al., 2013a). It uses nested equations which mainly relate to the labour market. A set of parameters are estimated which relate to the explained part of the equation, an error term is also included. Without the error term the calibration method will only select those with a high probability of having certain characteristics, i.e. based on a combination of characteristics it would go with the most probable. Even after this process there may still be unexplained spatial heterogeneity. The unconstrained variables may have a poor relationship with the constrained variables. To overcome this issue the variables simulated during the Monte-Carlo Simulation are calibrated to exogenous constraints. These external totals used in this calibration process come from census small area data. Correlation coefficients are calculated between the SMILE data and the external data for each of the labour market variables. These results are adjusted so they match the external data. In calibrating income, attention is required as adjustments can have implications on the distribution. A ratio of average income by source to the national average is utilised in the SMILE model to ensure the underlying distribution of incomes is kept (Morrissey and O'Donoghue, 2011). The synthetic data is also calibrated to be consistent with county level income data from the CSO. Absolute values are used so that the distributional characteristics of the survey data are maintained. This calibrating allows for unobserved spatial heterogeneity and ensure the same CSO county ratios are maintained (O'Donoghue et al., 2013b).

A spatial microsimulation methodology has enabled a spatially rich micro-dataset be created. This dataset contains individual level data on socio-economic and demographic characteristics as well as income measures such as market income, disposable income, taxes paid and social transfers received (Morrissey and O'Donoghue, 2013). The calibration and alignment techniques ensure that the data presented in SMILE is representative. Such data enables us to deepen our understanding of the spatial determinants of welfare.

2.2 SMILE model

It is the purpose of this chapter to give an insight into the rationale, development and application of SMILE in analysing the spatial incidence of welfare and income redistribution in Ireland. The following section gives an overview of Irish data availability. The SMILE model is then introduced. Quota sampling is described also in more detail. The calibration procedure to ensure income distributions are aligned to welfare measures external to the synthesis process is also explained. The application of SMILE to measure the spatial incidence of income redistribution in Ireland is illustrated. Finally the new monetary and non-monetary spatial measures of welfare which have been incorporated into the SMILE model and simulated dataset are introduced.

Micro-level data availability in Ireland

Micro-level analyses of income and welfare in Ireland have largely been overlooked due to the non-availability of income microdata at the small area level. Census micro data is available, but this data is unsuitable due to a lack of information on household composition and income, whilst also employing an aggregate spatial scale. National Accounts data present the most accurate representation of income, but this data is only available at the aggregate county level. The Living in Ireland survey (LII) contains income and employment information at the individual and household level. The 2000 dataset contained 13,067 individuals and information on a variety of individual, demographic and socio-economic characteristics, including income, employment and household composition statistics. However, this data is only available at a coarse spatial scale. The LII contains two location variables, a NUTS3 regional variable (containing eight regions) and a twelve category locational variable, categorised into the five cities in Ireland, a category for Dublin County, an 'open-countryside' category, and five categories for towns of varying sizes. The LII survey has since been replaced by a new survey, EU-SILC. EU-SILC has been collected in Ireland since 2003 with a typical sample size of 5,000-6,000. It is similar to the LII survey in that it collects data on income, health, labour and education to name a few. In contrast, the Irish Small Area Population Statistics (SAPS) contains census information disaggregated to the electoral division (ED) level. The 3,440 EDs represent the second most disaggregated spatial scale in Ireland; the new small areas being the most disaggregated. The population in any one ED ranges from a low of 55 individuals to a high of 14,238, with an average across all EDs of 885 (Morrissey et al., 2008). However, as with most censuses, data available on income and welfare is limited. If SILC data could be merged with the ED-level Census data, a spatially referenced micro-dataset containing the estimation of Irish income, labour and welfare distributions at the local level may be created. This provides a much richer dataset at a very local level of spatial resolution. Spatial microsimulation techniques are employed to create such a model, known as SMILE.

Introducing SMILE

SMILE is a static spatial microsimulation model, designed to simulate regional welfare, income, and labour distributions and thus provide a basis for regional economic analysis in Ireland (O'Donoghue et al., 2013a). As with similar international microsimulation models (e.g. Ballas et al. (2005a); Chin et al. (2005); Edwards and Clarke (2009)), SMILE may be used to provide government, policy-makers and non-government organisations with detailed spatial data which could be used to improve policy-making, resource targeting and to analyse sectoral and regional investments.

Background

SMILE has been developed through a collaborative process between the Universities of Leeds, Sheffield and Galway and the Rural Economy Development Programme

(REDP)[3] of Teagasc. The model was developed to enable the impact of rural development policies be assessed ex post and also new policies be assessed before they are implemented (O'Donoghue et al., 2013a). The initial steps involved estimating population developments (Ballas et al., 2001). Other elements were then added to the model such as population dynamics (Ballas et al., 2005b), accounting for farm size (Ballas et al., 2006b) and estimation of small area incomes (Morrissey and O'Donoghue, 2011, Shrestha et al., 2007). In addition to these elements components have been added to examine access to GP services (Morrissey et al., 2008), methane emissions from agriculture (Hynes et al., 2009b), recreational activities (Cullinan et al., 2006), GHG emissions (Grealis, 2014) and wave energy (Farrell et al., 2015). Over time this resulted in a comprehensive model that can be used for detailed spatial analysis in a number of areas. This thesis introduces a number of new elements to the model in the form of non-monetary welfare components. An intertemporal model is introduced which allows analysis of the SMILE model over time. Using the EU SILC it is possible to carry out an intertemporal analysis but you are unable to carry this analysis out across space. There are changes over time particularly in times of crisis and it is important to be able to analyse these changes both over time and across space. Such an analysis has not been carried out before. Typically you have temporal in surveys but not temporal with spatial data. We are extending intertemporal and spatial, but not dynamically. There will not be an observing of individuals over time but rather the spatial dynamics. Next housing costs and benefits are included. Housing costs in the form of rent or mortgage paid and benefits in the form of the stream of consumption value gained from owner occupation. This imputed rent is the benefit in-kind received from owning a property. Other benefits derive from reverse mortgage payments available to retirees. In this case the value of the property can be drawn down over time. The costs associated with commuting and the impact on employment income is incorporated. A farm viability measure is introduced and the impact of local labour markets assessed and finally a measure of local environmental characteristics and life satisfaction is calculated at the individual level.

SMILE Methodology

In attempting to synthesise SMILE there are a number of techniques which may be used. Ballas et al. (2005a) provide a complete overview, with Iterative Proportional

[3] Formerly the Rural Economy Research Centre (RERC)

Fitting (IPF) and various Combinatorial Optimisation (CO) methodologies being of greatest prominence. When deciding on which procedure to employ the primary objectives of importance the capacity to handle a combination of individual and household constraints and adequate run-time efficiency. The merits of existing procedures will now be discussed relative to these objectives.

Iterative Proportional Fitting (IPF) is a method for reconstructing tables from marginal control totals. In its most basic form, the IPF process can be viewed as a method to adjust a two-dimensional matrix iteratively until row sums and column sums equal some predefined values, and in a geographical context it can be used to generate disaggregated spatial data from spatially aggregated data (Wong, 1992). It has been found that IPF can potentially produce unrealistic data (Norman, 1999) as probabilities are used to create synthetic micro data from regional aggregates, rather than using real survey data. Although computationally efficient, it has been found that IPF is difficult to utilise when the unit of analysis of the constraint and the micro data are different.

Combinational Optimisation (CO) techniques overcome the synthesis issues of IPF by reweighting existing microdata to generate small area population data. CO techniques may be either deterministic or probabilistic in nature. Deterministic reweighting assigns weights to each household based on the probability of that household belonging to the region in question (Ballas et al., 2005a). Similar to IPF, deterministic reweighting algorithms are computationally efficient. Such algorithms are unsuitable for SMILE, however, as multiple units of analysis require non-trivial methods of weight generation, such as generalised regression weight based methods, an example of which is GREGWT, developed by the Australian Bureau of Statistics (Bell, 2000). GREGWT is a constrained distance minimisation function which uses a generalised regression technique to get an initial weight and iterates the regression until an optimal set of household or individual weights for each small area is derived. Williamson (2009) highlights that when there are large numbers of constraints, the GREGWT does not always converge.

Alternative to deterministic reweighting are probabilistic reweighting processes, the most popular of which is Simulated Annealing (SA). SA allows for data and constraints with different units of analysis to be employed. Unlike IPF, SA contains mechanisms to avoid becoming trapped at local minima (Wu and Wang, 1998). It is also less sensitive to convergence issues. Williamson (2009) found that in an Australian simulation, SA performed slightly better at matching than GREGWT for both constrained and unconstrained variables. This was particularly the case in districts where there was no convergence.

The main disadvantage of SA is the computational intensity due to the degree to which new household combinations are tested for an improvement in fit during simulation. To illustrate, Hynes et al. (2009a) found that it took two days to generate almost 140,000 individual farm records from 1200 survey data points on a 2G workstation. Scaling this computational requirement to a population of 4 million people using a greater number of constraints, the simulation of SMILE may take a number of months. This restriction is made even more burdensome as it is desired to carry out repeated simulations for sensitivity analysis and simulations of future population projections.

Thus, the constraint of computational intensity has limited the application of SMILE under SA, motivating the development of a more efficient algorithm focussed on improved efficiency through a reduction in the number of required computations. We call this process Quota Sampling.

Quota Sampling (QS) is a probabilistic reweighting methodology developed by Farrell et al. (2010). Similar to the process of SA, 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. The QS process is apportioned into a number of iterations, based on an ordered repeated sampling procedure. 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.

Lack of spatial microdata has significantly limited spatial analyses of welfare in Ireland. This chapter describes the approach taken in SMILE and how an Irish spatial microsimulation model has overcome this issue. It illustrates how within and between region welfare analyses at the small area ED level may be achieved as a result.

As the household has been deemed the most appropriate unit of micro-level welfare analysis, a greater level of complexity is imposed on the choice of simulation process. The means by which SMILE has accommodated this requirement has evolved as successive versions have been developed, Initially, IPF had been employed (Ballas et al., 2006b), but a desire to employ actual microdata motivated the use of SA procedures in the version that followed (Morrissey et al., 2008). SA, however, is computationally intensive and thus precludes the use of repeated syntheses or development of future projections. As a result, the development of the current version of SMILE involved the creation of a computationally efficient method known as Quota Sampling (Farrell et al., 2010). For a detailed discussion on the quota sampling methodology used in SMILE, the process of validation and calibration of the model see Farrell et al. (2013b).

As with all spatial microsimulation models, the credibility of results relies on how well actual population distributions are emulated. In order to ensure reliability of estimated welfare distributions, SMILE uses extensive validation procedures. The performance of quota sampling is assessed using both in-sample and out-of-sample validation. Whilst the validation results are quite good given that different datasets were used, an issue in relation to unexplained spatial heterogeneity remained which prompted a calibration procedure. This is carried out in two steps whereby an accurate distribution of labour force variables is simulated. Followed by an alignment procedure whereby market incomes are readjusted to be representative of national accounts. On completion of the alignment process, SMILE offers a fully representative profile of labour force participation and market incomes at both the household and small area level. In the absence of actual small area microdata, calibration ensures the most reliable estimation of spatially referenced microdata.

Upon the creation of this platform, the spatial distribution of income and the impact that the tax-benefit system has on changing this distribution has been estimated. Using SMILE results it was found that disposable income is on average lower in rural than urban areas with transfers from urban to rural areas. These results correspond to those of Morgenroth (2008) who developed an analysis of the regional transfers across the country. Morgenroth's analysis shows that there is a transfer of resources from the GDA and South West regions of the country to the rest of the country.

As such, this chapter has demonstrated how a profile of disposable income in rural Ireland is achieved through the use of spatial microsimulation techniques. Integrating this data within a GIS provides policy-makers with small area level maps of income. These maps in turn can deepen our understanding of the determinants of inequality and poverty and lead to improvements in the design of policies tailored to local conditions.

The spatial detail in SMILE also allows for further location specific information to be added to the model to enhance our understanding of welfare.

2.3 Building on SMILE

So far what has been mentioned in relation to SMILE has already been developed. The creation of spatial microdata using SMILE has led to further studies and analysis which was previously not possible due to a lack of data. Areas such as disposable income, GHG emissions, farm viability, health services and recreation activities have been examined by building on the knowledge and microdata created using SMILE.

Like these previous studies mentioned this thesis updates SMILE to include additional spatial elements which give a more complete measure of spatial welfare. These new measures take into account time, space, capital and the environment. Using the spatial distribution of disposable income from SMILE as a base measure, we assess the impact of each additional measure on the spatial welfare. The sensitivity and impact on the distribution is analysed for each of the new measures incorporated into SMILE.

This thesis builds on the work already carried out by researchers on the SMILE and updates SMILE by adding a number of additional components. These components, each unique, will have to be gathered and calculated using a variety of spatial econometric and geocomputation techniques and methods. In total there are five additional components added to the SMILE model.

- Intertemporal analysis
- Housing costs and benefits
- Commuting Costs
- Farm viability and local labour markets
- Spatial environmental attributes of the area

The following sections outline the some of the techniques and approaches used. Where previous models and studies fell short or where they were restricted and the justification behind why each component is interesting, will be discussed. The components cover a broad range of issues such as intertemporal trends, non-monetary income, spatial inequality, in-kind benefits, capital accumulation, urban sprawl, threats to agriculture, happiness and life satisfaction and the value of place. Combined together these components will tell us more about the spatial drivers of welfare. Due to the spatial nature of the data spatial methodologies were employed.

Decomposition Index

In order to examine spatial inequality and segregation a method of measuring must be chosen (OECD, 2016a). Differences will exist not only between regions but within regions between people. We can identify areas of segregation when there are large levels of variability between regions (Shorrocks and Wan, 2005). Using this data measures of segregation and inequality such as the dissimilarity index, spatial ordinal entropy or Theil index (Shorrocks, 1980, Shorrocks, 1982) enable us to better understand the composition of areas. These measures enable us to identify the areas worst affected and the level of inequality that exists between areas. The Theil index enables us to analyse population subgroups. Inequality can be easily decomposed into the amount of variability attributed to the different population subgroups. In our case we will examine the amount of variability attributed to between areas (Electoral Divisions) and then within areas between households.

If one regards the set of all annual incomes as the total population, where the groups are individuals or households, then one can decompose total variability of incomes into a factor attributed to between areas (between group variability) and variability within areas between individuals (within group variability).

Defining Welfare

This focus of this thesis is on the spatial distribution of welfare. Welfare however can take on several different definitions, income, wealth, well-being, happiness, mental health, general health.

In this thesis, a spatial distribution of equivalised household disposable income will form the base measure. Equivalised income is used as it considers the size of the household. To this base measure we add other various components and measures such as the monetary costs and benefits of home ownership in the form of imputed rent. This goes some way towards factoring in an individual’s or household’s wealth into the analysis. A measure of happiness is also added. Including happiness takes into account a non-monetary aspect of welfare. Finally, we also included monetary costs of commuting.

It would be incorrect to include all of these measures under the umbrella term of income, therefore the term welfare is used instead as we are considering more than just monetary income in our analysis.

Equivalence Scale

The needs of a household increase with each member however this is not at a constant rate due to economies of scale. There will be large fixed costs such as housing and utilities which will not increase proportionally for each additional household member. Therefore in order to take into account the size of the household, an equivalence scale is used. This will assign a weighting to members of the household based on age and number of household members. A range of equivalence scales exist, all with the same goal of taking into account household size (Atkinson et al., 1995).

Table 2-1: Equivalence Scales

Name	First Member	Additional Adult	Additional Child
OECD or Oxford Scale	1	0.7	0.5
OECD-modified Scale	1	0.5	0.3
Square Root Scale	Square root of household members	N/A	N/A
National Scale	1	0.66	0.33

Source: OECD (2014b), CSO (2014a), Callan et al. (1996a)

For this thesis the National Scale is used (also known as ESRI equivalent scale A). This scale was chosen as it is the equivalence scale most widely used in Ireland (CSO, 2013, Nolan et al., 2002) and gives consistency across difference sources (Callan et al., 1996a). For this scale an adult is defined as being over the age of fourteen.

Spatial Scale

In deciding on what spatial scale to use it was decided to examine welfare at the Electoral Division scale. Since 2011 Census SAPS are available at a new, more spatially disaggregated unit, Small Areas (SA). These SAs have a minimum size of 65 households to ensure data confidentiality (Charlton, 2007). However only the ED level is considered as SA level SAPS data was not available for the years 1996, 2002 and 2006, which would be problematic for the intertemporal analysis paper. Also the SMILE model output is at the ED level. For this reason ED was used as the spatial unit of analysis. In the Republic of Ireland there are currently 3,440 EDs. Of these EDs 32 have a very low population so for confidentiality reasons they are amalgamated into neighbouring EDs by the CSO. As a result only 3,409 EDs appear in published Census data. It should also be noted that in this thesis we only examine the spatial distribution of welfare for the Republic of Ireland and not for the Island of Ireland. Table 2-2 shows the various geographic units in Ireland in descending order. All units listed in the table all follow along the same boundary line, i.e. they overlap perfectly. They can then be easily aggregated and disaggregated depending on the analysis. The generalised 20m shapefiles are used in this analysis.

Table 2-2: Administrative Areas Ireland

Geographic Unit	Number of Divisions
Small Area	18,488
Electoral Division	3,409
Local Authority	34
County	26
NUTS 3	8
NUTS 2	2
NUTS 1	1

Urban Rural Classification

EDs are largely used in this thesis to summarise the various results. However it is not practical to list 3,440 EDs when reporting summary statistics. Likewise having a map for each summary statistic would not be the most efficient method. It is therefore important to have some means of reporting results from the analysis in a table which is easily presentable to the reader. County or Local Authorities could be used however the harsh boundaries are not good at presenting results particularly in the GDA. In order to summarise the results of the various papers in an efficient and effective manner an urban rural classification was created. This classification helped to group EDs that were similar geographically into the one class or category. This classification is loosely based on the Teljeur and Kelly (2008) urban rural classification system. Using the Census 2011 Settlements Boundary data EDs were classified into one of ten categories. An ED is assigned to a category if 50% or more of its area is contained within the settlement boundary.

Spatial Analysis - Commuting Data

SAPS data is the only population data source for Ireland with detailed individual and household information. This data however contains no income information. In contrast, the SILC is a nationally representative survey containing 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, which contains two regions, the Border, Midlands and West region and the South East region). As such, any analysis using the SILC survey is constrained to the national level. Using a matching algorithm to link the data in the SILC with the small area level SAPS data, a much richer dataset would be obtained that would allow an examination of disposable income across the Irish regions. One can use spatial microsimulation techniques to accomplish this.

The development and application of spatial microsimulation models offers considerable scope and potential to analyse the individual composition of an area so that specific policies may be directed to areas with the greatest need for that policy (Birkin and Clarke, 2012). The Simulated Model of the Irish Local Economy (SMILE) is a spatial microsimulation model. The first version of SMILE, referred to as SMILE2002 for the purpose of this paper, was based on 2002 Census of Population data and the Living in Ireland Survey (2001) and used a combinational optimisation algorithm, simulated annealing (Morrissey et al., 2008). However, although 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 the simulation (Farrell et al., 2013a, Hynes et al., 2009b). As a result, to create SMILE 2006 and match the Small Area Population Statistics (SAPS, 2006), SILC (2005) and POWCAR (2006) datasets a more computationally efficient method known as quota sampling was developed by Farrell et al., (2013). For a complete technical overview of the SMILE 2011 and the Quota Sampling methodology please see Farrell et al. (2013a).

SMILE creates synthetic data. As such, validation of the output created by SMILE is an integral component of the model's construction. Calibration through alignment (Morrissey and O'Donoghue, 2011, Morrissey et al., 2013) offers a method to ensure that the output produced by the SMILE model is consistent with real world data. A full description and application of the calibration method in terms of labour force and income distributions and socio-economic characteristics and health service utilisation is provided by Morrissey and O'Donoghue, (2011) and Morrissey et al., (2013), respectively. Calibration through alignment was used to ensure the income estimates used in this thesis are accurate. Post calibration, there is a population dataset which contains income and demographic data at the ED[4] level. On linking the POWSCAR dataset to the SMILE data we have a dataset which contains individual socio demographic and economic information as well as information on their commuting time, distance and mode.

2.4 Spatial Analysis Techniques

The dataset produced using spatial microsimulation does not contain any detailed spatial information on levels of housing benefits or costs, commuting times, commuting costs, income from spatial attributes or others impacts of place such as local labour markets. Many of these components which should be included in a comprehensive measure of welfare face similar issues to disposable income such as a lack of spatial data. To overcome these issues spatial methods are applied to interpolate and estimate property prices, rental prices, commuting times, commuting distances, level of service provision, environmental attributes and life-satisfaction levels at a detailed spatial scale. As there is a large spatial element to this thesis a number of spatial analysis techniques are employed. These methods have led to creation of new spatial datasets not previously available.

Geographical Information Systems

A geographical information system (GIS) is a powerful software tool which allows detailed spatial analysis to be carried out. Using GIS allows the creation of new data rich datasets by linking or enhancing existing data. Particular features or points can be geocoded visually or areas can be classified based on proximity to another area. Its ability to merge, intersect and join enables the user to answer location based questions.

To avoid any spatially mismatches, careful consideration has been taken in projecting layers so that they have the same coordinate system, IRENET95 (Irish Transverse Mercator) as opposed to the older TM75 (Irish Grid).

[4] Since 2011 SAPS are available at a new, more spatially disaggregated unit, Small Areas (SA) of which there are 18,488. We however will only consider the ED level as there have been some issues around microsimulating at the SA level.

Kriging

One of the biggest issues with researching at a disaggregated spatial scale is the lack of data. Often datasets are at an aggregated scale such as county or NUTS 3 or only national data may be available. There are issues around confidentiality concerns over publishing data at a small spatial scale. To overcome these issues spatial interpolation methods can be used to estimate variables at unobserved locations using data in observed locations. There are many techniques which can be used such as nearest neighbour interpolation, inverse distance weighting, pycnophylactic interpolation or kriging. All operate on the concept of Tobler's first law of geography, "everything is related to everything else, but near things are more related than distant things". Interpolation is a method of data smoothing, smoothing out the data between points taking into account distance between points and weighting accordingly. The kriging methodology used in this thesis was conducted in the software package R. We opted for the kriging methodology as it is the one most used in the literature and tends to provide the best estimates (Anselin and Lozano-Gracia, 2008).

The kriging methodology employed is used to interpolate or smooth spatial data (Diggle et al., 1998). It is often used in spatial statistics (Cressie, 1990) and has been used to estimate house prices (Montero and Larraz, 2010). Kriging operates on best linear unbiased prediction (BLUP) (Goldberger, 1962) while at the same time taking into account spatially correlated data. It is based on Tobler's Law that everything is related to everything else but nearer things are more related to each other (Tobler, 1970). It takes account of this by placing a greater weight on observations which are closer to each other.

Kriging assumes we can estimate the variance-covariance matrix as a function of distance only. When applied, kriging creates a smooth interpolation surface between the points which are measured. The variance-covariance matrix is estimated by firstly computing a variogram (Pace et al., 1998). The pair-wise squared differences among all errors, are plotted against the distance between the pair points (Bailey and Gatrell, 1995). We can assume there is a boundary where the distance is greatest and at which the value of one point is related to the value of another point (Hoshino and Kuriyama, 2010). As distance increases the covariance converges towards zero. The points beyond this range will have zero impact on the points inside the range or boundary. In kriging a greater weight is given to points which are closer in distance to the dependant (Dubin et al., 1999). Kriging is often used to estimate real estate values (Hoshino and Kuriyama, 2010, Pace et al., 1998, Dubin et al., 1999, Dubin, 1992, Basu and Thibodeau, 1998). The variogram in the model takes account of this by placing more weight on the values of the objects which are closer. The level of weight decreases at an increasing rate until objects are at a distance where there is no effect on the value estimated.

In estimating housing costs a number of data sources are utilised. Table 2-3 shows a cross section of the Department of Housing, Planning and Local Government (DHPLG) data. This data is very spatially aggregated. The only areas it has been spatially disaggregated for are the local authority city areas of Cork, Galway, Limerick and Waterford. Dublin represents county Dublin. These average house prices are derived from data supplied by the mortgage lending agencies on loans approved by them rather than loans paid. In comparing house prices figures from one period to another, account should be taken of the fact that changes in the mix of houses (including apartments) will affect the average figures (Department of Housing, 2016). Data on average second price house prices is also available and the time period for both datasets is 1969-2015. There is also no information on the characteristics of the house. The only available data is whether it is a house or apartment.

Table 2-3: Department of Housing, Planning, Community and Local Government Average New House Prices (2000-2011)

Year	Annual New Property prices (includes houses and apartments) €						
	National	Dublin	Cork	Galway	Limerick	Waterford	Other Areas
2000	169,191	221,724	166,557	163,824	145,834	145,713	154,050
2001	182,863	243,095	174,550	171,161	152,205	155,488	166,834
2002	198,087	256,109	184,369	187,607	168,574	167,272	179,936
2003	224,567	291,646	211,980	223,388	197,672	195,173	203,125
2004	249,191	322,628	237,858	242,218	210,868	220,286	228,057
2005	276,221	350,891	265,644	274,905	226,393	246,914	254,006
2006	305,637	405,957	305,015	286,176	275,411	271,521	276,570
2007	322,634	416,225	325,453	300,750	288,202	292,057	296,605
2008	305,269	370,495	314,276	292,777	276,719	288,478	282,677
2009	242,033	260,170	252,011	236,113	260,684	227,444	231,739
2010	228,268	251,629	244,333	219,459	224,778	224,021	218,097
2011	230,303	290,668	241,502	229,558	216,307	205,598	216,400

Additional spatially disaggregated house price data is available from the Daft.ie quarterly report.

Table 2-4: Daft.ie Average House Prices Q2 2011 (in '000s of €)

	Number of Bedrooms				
	1	2	3	4	5
Dublin City Centre	124	192	245	0	0
Dublin North City	136	185	246	385	519
Dublin South City	146	202	261	446	657
Dublin North County	154	177	228	405	636
Dublin South County	185	267	351	541	738
Dublin West County	104	152	204	278	393
Meath	109	128	175	266	375
Kildare	89	139	183	292	389
Wicklow	130	176	229	327	448
Longford	20	78	112	174	183
Offaly	56	109	135	207	285
Westmeath	44	115	136	200	263
Laois	50	81	123	178	308
Louth	71	105	152	245	319
Carlow	39	104	148	220	296
Kilkenny	20	107	144	212	299
Wexford	64	101	147	210	270
Co. Waterford	0	94	178	264	334
Waterford City	61	88	139	220	286
Kerry	100	135	174	237	309
Co. Cork	82	132	167	252	330
Cork City	121	144	196	291	399
Clare	39	111	148	226	271
Co. Limerick	87	108	149	246	287
Limerick City	77	120	169	233	266
Tipperary	36	105	144	223	257
Co. Galway	50	125	152	199	248
Galway City	120	167	190	241	357
Mayo	77	112	144	196	254
Roscommon	60	87	118	166	215

Sligo	62	111	134	188	244
Leitrim	31	85	120	168	189
Donegal	34	84	132	190	232
Cavan	30	94	128	190	236
Monaghan	15	82	137	218	235

Source: Lyons (2011)

Table 2-4 shows data for Q2 2011. The data is spatially disaggregated to the county level with additional disaggregation in Dublin. More information is also given in regard to house characteristics and the number of bedrooms is included. Zero values are given where there is not enough data. This data however is based on list prices and not actual house sales. It is very unusual for house prices to exceed their list price and list prices are often used as the upper bound. Haurin et al. (2010) found that on average the list price exceeded the sales price by 3.7%. Using the house price trend from the Daft.ie report we assume a similar trend exists for the DHPLG data. For example using these assumptions it is possible to estimate the price of a two bed house in Dublin North City in 1985. A three bedroom semi-detached house is indexed as the average house. This makes it possible to overcome the lack of spatially disaggregated house price data. To further disaggregate by area, we use the rental price pattern created using the kriging methodology to estimate house prices at the ED level. The objective of estimating this data is so it can be used to estimate a household's mortgage repayments when this information is missing. To be able calculate these payments information is required on how much the house was purchased for.

OD Cost Matrix

As the journey times and distances in the POWSCAR data are stated by the respondent, there may be an element of inaccuracy associated with this data. It is necessary to generate accurate data in this regard. To generate journey times and distances an Origin Destination (OD) cost matrix is created. This is calculated in Arc GIS using the spatial analyst tool. The process begins by firstly creating the road network dataset on which the travel times and distances are calculated. The road network data comes from the Open Street Map dataset which is open source. Before the road network can be converted into a network dataset, it must be cleaned. All non-roads are removed such as driveways, footpaths and cycle lanes. To determine the length of time it takes to travel a segment of the road information is needed around the speed the vehicle travels at. Average speed values are used with these values attached to each road segment based on the road class. This data comes from the Road Safety Authority free speed survey (RSA, 2013). Where the road class was unknown the lowest class of road was used.

Using this information and the length of each segment of road it is possible to calculate the time it takes to cover that distance going at that speed.

$$\text{Time} = \text{Length of Road} * (60 / \text{speed})$$

Once this process is complete the road data is ready to be converted into a Network Dataset. There are a lot of options one can choose during this process, you decide whether you want to model turns, add restrictions such as one-way streets and traffic lights and you can also ban U-turns. You also specify on which fields the impedance will be. In this case both time and distance are important so both are used. The origins and destinations used in the model were the ED centroids. The ED centroids were used as opposed to individual houses for a number of reasons. Firstly we cannot tell from the POWSCAR what type of house an individual lives or where it is located. The only information in the data in relation to location is the ED residence and the ED of place of work. Were individual addresses from the Geodirectory used as the origins and destinations the exercise becomes very computationally intense. Also the weighted residential centre of an area would not correspond to the employment centre of an ED. The centroid is therefore the best compromise given the level of computing power available and the information contained in the POWSCAR. Even using the 3,440 EDs, that leaves 11,833,600 different combinations of origin to destination. The EDs were subdivided and the model re-run as a batch process to overcome issues around lack of RAM. Other issues encountered were in relation to road segments which were disconnected from the national road network. When the ED centroids are loaded as origins and destinations their location may not correspond to a road segment so the point is “snapped” to the road network. However in a small number of cases the road segment it snapped to was disconnected. In each of these cases the disconnected road segment (which was often a minor roadway or track) was deleted. Upon completion of the OD cost matrix the times and distances were merged back into the POWSCAR dataset. As SMILE has been linked to the POWSCAR data, it makes it possible to calculate commuting costs as a percentage of an individual’s income. The costs of commuting will consist of both monetary and non-monetary aspects. The monetary costs will be the costs of running the vehicle including insurance, tax, maintenance and fuel costs. Where a commuter uses public transport, costs per km which reflect the costs imposed in that area are used. E.g. public transport costs in Dublin versus Galway. This will be the focus of chapter 5.

Geocoding

Some data was unavailable such as local rental values. This data was stored in a table and with just a string location variable. Before this could be used in any spatial analysis it would first have to be geocoded with an x y value assigned to each point in the data. In the case of the rental locations from the PRTB, these were geocoded using the Geodirectory. Locations were assigned to the centroid of all buildings matching the address from the PRTB. Outliers were ignored so as not to skew the centroid point. Other useful method of geocoding is by using OSi map viewer and manually recording the co-ordinates. Satellite imagery can also be utilised through the map viewer which is particularly useful for environmental aspects such as beaches.

Conclusion

Using the output from a spatial microsimulation such as SMILE has enabled issues such as a lack of income data at a spatial scale to be overcome. Using this synthetic micro dataset from SMILE it is possible to enhance SMILE by including additional spatial data. A number of components are added which allows for the sensitivity of welfare to welfare definition to be examined at a spatially disaggregated scale. Components which are added include; intertemporal, housing, commuting, local labour markets, spatial attributes and flooding disruption. The follow chapters each focus on one of these additional welfare components. The impact on welfare both within and between welfare is examined.

Chapter 3. Intertemporal Income in Ireland 1996-2011 – A Spatial Analysis[5]

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3.1 Abstract

In this paper we employ a microsimulation approach to examine four census years (1996, 2002, 2006 & 2011). Using spatial microsimulation and GIS methods we create a spatially rich dataset for each year which is then used to create a spatial distribution of disposable income. The period covered in this paper is an important time in Ireland's history and this paper takes a spatial perspective on the significant changes in the landscape of disposable income. By adopting this approach we can examine if there are clear disparities between different areas of the country. From our results we have showed that there are significant differences in how regions have performed during this period 1996-2011. The major urban centres and hubs have outperformed the rural areas in terms of levels of disposable income. Even amongst urban areas, Dublin has outperformed all other areas becoming an outlier such is the difference in levels of disposable income. The Celtic Tiger, Property Bubble and Great Recession have all impacted on the different regions in different ways.

KEYWORDS: Small area, microsimulation, intertemporal, inequality, income.

JEL classification: C15, D31, H23, H31, I32, P25, R12.

3.2 Introduction

In this paper the distribution of disposable income will be examined in a spatial context. Disposable income is not homogenous across space therefore it will be influenced across place (Kilroy, 2009). There are structural differences between regions (Heshmati, 2004) such as local specific policies (Shankar and Shah, 2003), local labour markets and agglomeration effects . There exists a spatial dimension to the income distribution

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which can impact positively or negatively. It should be the aim of policy to reduce this inequality in the distribution of income.

The literature on spatial distribution of income is vast and diverse. Studies have focused on income at a regional (O'Leary, 1999), national (Slesnick, 2001) and international scale (Caselli, 2005). Some of these studies have focused on the clustering of poor/rich regions (Dall'Erba, 2005). The effect of policy on reducing regional disparities has been covered (Becker *et al.*, 2010). Different locations will therefore have different levels of income (Sommeiller, 2006).

The focus of this paper is intertemporal disposable income. We would expect the spatial distribution of disposable income to change due to factors such as migration between urban and rural areas. The pull factors of urban areas include higher wages (Fields, 1975), a perceived better quality of life, more career opportunities, furthering education and access to more services (Blomquist *et al.*, 1988). The pull factors in rural areas include natural environments, lower living costs, lower congestion and a more attractive lifestyle (Roback, 1982). These are countered by push factors such as higher living costs, higher crime rates, traffic congestion and pollution in urban areas and low education and employment opportunities in rural areas. As a result of these factors, wages are typically higher in urban areas.

The economic climate and labour market situation in a particular region affects the income distribution. Job losses can have a significant effect on a region. Similarly regions may benefit from agglomeration economies (Rosenthal and Strange, 2004), such as the clustering of industries and expertise in an area (Marshall, 1920). By observing spatial distributions over time, we can observe and attempt to track the changes in the spatial distribution of income.

The period covered in this paper was an economically turbulent period in Irish history. The Celtic Tiger (1995-2006) was a period of strong economic growth largely due to FDI. Real GDP growth averaged 10% a year (Honohan and Walsh, 2002). This period saw significant growth in the CPI. In the period 1996-2002, CPI grew by 18%, from 2002-2006 by 11% and 2006-2011 by 6%. Overall the CPI increased in the period 1996-2011 by 31%. The property bubble (2001-2007) saw house prices increase rapidly due to a combination of factors including; Government policy, banks' lending practices and media coverage (Donovan and Murphy, 2013). House prices more than quadrupled between 1995-2007 (Kanda, 2010). A combination of the global financial crisis and collapse of the property market caused Ireland to enter a deep recession with GDP decreasing by 8% in 2009 alone (Kanda, 2010). The so called "Great Recession" was felt more strongly in Ireland due to double shocks hitting at the same time (global financial crisis and collapse of property market). In the space of four years unemployment more than doubled (2007-4.7%, 2011-14.6%) and net government debt increased 8 fold (2007-10% of GDP, 2011-81% of GDP), primarily through bank bailouts. This is in contrast to the period 1994-2004 where growth in real GNP was over 6% on average. In the same period unemployment fell from 15% to under 5% (Barrett and McCarthy, 2007). Whelan (2013), give a nice overview of the macroeconomic background in Ireland over the period 1988-2013, which additionally notes the impact of austerity measures on incomes. With this story taking place this paper aims to examine the changing distribution of income over this interesting time period which includes years of extraordinary growth as well as large contractions of the economy.

One of the results of the crisis are the so called "ghost estates" (residential units unfinished or abandoned) (Kitchin *et al*., 2010). Census data 2011 shows that there was an oversupply of housing, with approximately 15% vacancy rates (SAPS, 2011). This problem is especially bad in the former Upper Shannon Rural Renewal Scheme area, where a building tax incentive scheme existed between 1999 and 2008. The area now contains 18% of all "ghost estates" (Kitchin et al., 2014).

Much of the story around this period has focused on the national scale. Not much attention has been paid to whether different areas were affected more or less than others. The NSS (2002) was a key policy document which aimed towards achieving balanced regional development in Ireland. However there was a lack of commitment to the strategy which saw it viewed as a document offering advice to policymakers and planners (Meredith and Van Egeraat, 2013). Another issue was the selection of the "gateways" and "hubs". There was disagreement over the selection of some cities and towns over others. It was seen as "winners" and "losers" type selection policy (Daly and Kitchin, 2013). The CEDRA report (CEDRA, 2014) detailed specific recommendations on how to improve rural areas. With this in mind it is important to note the political sensitivities around stating one place should be developed over another. Meredith and Faulkner (2014), examined the geography of the labour force in Ireland 1991-2011 but found little change in labour characteristics of areas over this period. This paper builds on this by examining changes in income over time.

In this paper we examine spatial characteristics at the electoral division (ED) level. There are 3,440 EDs in Ireland, with an average population of around 1,345 in each. In order to examine income at the ED level we will require appropriate data. A Spatial Microsimulation approach helps us in overcoming the lack of ED level income data in published Census data. The follow section outlines the Spatial Microsimulation process.

3.3 Methodology

Distribution of Income

Disposable income is used as a proxy for welfare. Disposable income will consist of income generated from employment, non-work income such as income generated from investments, social benefits and then less any taxes.

$$Y_i = w_i + f_i + b_i - t_i$$

Where Y_i is an individual's total personal income, w_i is employment income, f_i is non-employment income such as investments, b_i are social benefits and t_i any taxes (includes tax on employment income, non-employment income and social benefits).

Disposable income is examined for four census years; 1996, 2002, 2006 and 2011. Over this period inequality remained relatively stable with a mean Gini coefficient of 0.311 and standard deviation of 0.01. Average disposable income in Ireland has increased by more than 300% in real terms since the 1980s. Given this information it would seem that the population's disposable income has increased at a constant rate for all groups (OECD, 2013).

Spatial Microsimulation

To generate a spatial distribution of income we require income data at a meaningful scale. Spatial Microsimulation has a number of advantages over published aggregate totals. It can be linked to other datasets, can be spatially disaggregated or aggregated, data is stored as lists and the models developed can be updated (Ballas et al., 2006b). Normally there is a lack of income data contained in small area census data; however there is detailed additional spatial information. The opposite is true of survey data; it contains data on income but has poor spatial detail. Spatial microsimulation helps in overcoming these problems. This paper uses the output from the SMILE model. SMILE is a static microsimulation model (Morrissey *et al*., 2013) which has been developed by the Rural Economic Development Programme, Teagasc and the School of Geography at the University of Leeds (Morrissey *et al*., 2008). The SMILE model aids in creating a spatially disaggregated population micro-dataset with detailed income and spatial information. It does this by matching overlapping variables between the census and survey datasets (Morrissey *et al*., 2008). SMILE uses quota sampling (QS), which is a probabilistic reweighting method (Farrell et al., 2012b). It works by firstly randomly ordering the micro data, it then samples from the micro data until the quotas - which are set by the constraint variables from the census - are filled. This data is then calibrated to ensure that the data is representative. Once calibration has been performed, SMILE presents us with a dataset which contains market income as well as other demographic information at the electoral division (ED) level for each individual in the population.

Tax-Benefit System

This micro-dataset created by SMILE contains socio-economic, demographic, labour force and income information at the individual and household level which is also spatially referenced. For an in-depth discussion on the SMILE model see (Morrissey and O'Donoghue, 2013, O'Donoghue et al., 2013a). The SMILE model also takes into account the complex nature of the tax-benefit system. Income is modelled net of taxes and benefits. In order to do so a static microsimulation model of the Irish tax-benefit system was developed. In Ireland a number of similar models have been developed such as the SWITCH model (Callan et al., 1996b) as part of a European tax-benefit model (O'Donoghue, 1998). A simplified Tax-Benefit microsimulation model was programmed in Stata to model the spatial distribution of income net of taxes and benefits. This model is consistent with other publicly available models such as EUROMOD. SWITCH is not publicly available. The tax-benefit system is simulated for each of the census years. For a technical overview of the process please refer to (O'Donoghue et al., 2013a). This component of the SMILE model is important as the distribution of our disposable income measure relies upon, not only the distribution.

Equivalence Scales

Typically income is adjusted to take account of the varying composition of households. Equivalence scales are often used to overcome this issue. Income is measured at an equivalence scale to take account of the need of the household. Although there are many scales (OECD, 2014b), we use the national equivalence scale as this is the one which is widely used by the CSO in its SILC reports. This scale gives a weighting of 1 to the first adult in the household and 0.66 to each subsequent adult (>14 years). Children (<14 years) are each assigned a weighting of 0.33. These weightings are totalled to calculate the equivalised size of the household (CSO, 2014b).

The equivalised household disposable income is calculated for every household in the country. We then take the median equivalised household disposable income value for each electoral district. This represents the typical disposable income of a household within that ED.

Geographic Information System

Using GIS (Geographic Information System) namely ArcMap, maps of the spatial distribution of disposable income were created. The main advantage of maps is their ability to display tables of information in one figure. The spatial distribution maps display quintiles of median equivalised household disposable income. There is a map for each of the census years 1996, 2002, 2006 and 2011. The maps display the data using a standard electoral divisions shapefile from the CSO website.

3.4 Data

As mentioned previously the SMILE model contains survey and census data in simulating incomes. The survey data for the years 1996 & 2002 comes from the Living in Ireland (LII) Survey. LII forms the Irish component of the European Community Household Panel (ECHP). 3,174 households completed the survey in 1996. From 2001 a new sample of households was used, a total of 2,865 households completed the survey. Respondents answered a range of questions including those around income earned (Watson, 2004).

For the years 2006 & 2011 EU-SILC data is used. EU-SILC has been collected in Ireland since 2003 with a typical sample size of 5,000-6,000. It is similar to the LII survey in that it collects data on income, health, labour and education to name a few. Using LII and EU-SILC data allows us to overcome the problem of a lack of data on income in Census data such as the Small Area Population Statistics (SAPS). Although two survey datasets (LII and EU-SILC) are utilised, they both contain many overlapping variables with identical definitions. SAPS is census data which is available for the years 1996, 2002, 2006 & 2011 and contains population totals broken down by themes[6] at the ED level. Since 2011 SAPS are available at a new, more spatially disaggregated unit,

6 Themes include sex, occupation, and industry. All are totals at the ED level.

Small Areas (SA)[7]. We however will only consider the ED level as SA level SAPS data was not available for the years 1996, 2002 and 2006.

The advantage of using the data from SMILE over Census data only, is the extra information on income. Existing income data from the CSO is aggregated to county level. Although useful, it gives little indication as to how the distribution of income within each county varies spatially. The data from SMILE makes it possible to examine at a local level, ED in this case, which areas moved up and down the income distribution over time. It then allows us to identify the characteristics and drivers of these areas. Any reoccurring characteristics or drivers which emerge may prove useful in identifying areas most in need of state support and government resources.

Only EDs that are present in all four census years are used. This means that 47 EDs (1.2% of total EDs) which have been redrawn or amalgamated with other EDs and that were present in 1996, 2002 and 2006 have been excluded from the analysis. This still leaves us with 3,396 EDs.

Our results are examined in terms of using quintiles of median equivalised household disposable income. Examining disposable income will take into account the redistributive nature of the tax-benefit system. Using equivalised income takes into account the size of the household. Taking the median value for the ED will reduce the effect that outliers may have if we were to take the mean value as the income distribution does not take the form of a normal distribution. Using quintiles allows for the large number of EDs to be summarised in a single table. Quintiles are also useful at tracking an EDs movement over time on the income distribution.

Table 3-1 shows the results of a sensitivity analysis using other economic performance indicators. Quintiles were created using ED level tertiary education rate, labour force participation rate and employment rate. Comparing with the median disposable income quintiles created above we calculate how many EDs moved up or down a quintile when we use a difference economic indicator. The percentages show percentage of total population in 2011. For each of the three measures over 70% of the population remains around the one standard deviation of the mean. We are satisfied that the median equivalised household disposable income of an ED gives a good overall impression of the economic state of that area.

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[7] SAPS 2011 contains data on 18,488 Small Areas. There were 3,409 EDs that same year.

Table 3-1: Sensitivity Analysis (using 2011 data) – Quintile Movers

Moved	Education	Labour-force	Employment-rate
-4	0%	1%	0%
-3	4%	5%	4%
-2	7%	10%	9%
-1	17%	17%	18%
0	41%	33%	36%
1	20%	20%	20%
2	8%	10%	9%
3	2%	4%	3%
4	0%	1%	0%

Source: Author Calculations

An urban-rural classification system was created using the settlements shape file from the CSO. EDs were classified as urban or rural based on whether more than 50% of their area was located within a settlement of varying sizes. Table 3-2 gives a breakdown of the various urban-rural classifications. If an ED belonged to two classifications it was assigned to the one with the greater population density. This is an adaptation of the classification method used in (Teljeur and Kelly, 2008).

Table 3-2: Urban-rural classification breakdown

	1996 Persons	2011 Persons	% Pop. 1996	% Pop. 2011
Rural	628,359	791,644	17%	17%
Village (200 – 1499)	521,362	688,238	14%	15%
Town (1500 – 2999)	188,491	275,295	5%	6%
Town (3000 – 4999)	101,105	137,648	3%	3%
Town (5000 – 9999)	209,719	321,178	6%	7%
Town (1000 +)	704,805	734,120	19%	16%
Waterford[8]	44,009	45,883	1%	1%
Galway	59,456	91,765	2%	2%
Limerick	57,107	45,883	2%	1%
Cork	179,425	183,530	5%	4%
Dublin County	386,033	527,612	10%	11%
Dublin City	676,093	745,457	18%	16%

Source: Author Calculations

[8] Waterford, Galway, Limerick and Cork only include EDs inside the city boundary.

3.5 Results

The methodologies have allowed us to divide the population into small area groupings not previously possible and examine the changes in these groups over time and space. For our results we have calculated a spatial distribution map of median equivalised household disposable income between 1996 and 2011. These maps show quintiles of median household disposable income and are weighted by the population of the ED so that each quintile contains 20% of the total population.[9]

Table 3-3: Quintile Cross-Tab (in 2011 population %)

		1996					
		1	2	3	4	5	TOTAL
2011	1	42%	37%	14%	7%	0%	100%
	2	16%	32%	35%	15%	2%	100%
	3	14%	16%	29%	29%	12%	100%
	4	9%	9%	21%	38%	23%	100%
	5	1%	3%	5%	22%	70%	100%
	TOTAL	83%	96%	104%	110%	106%	

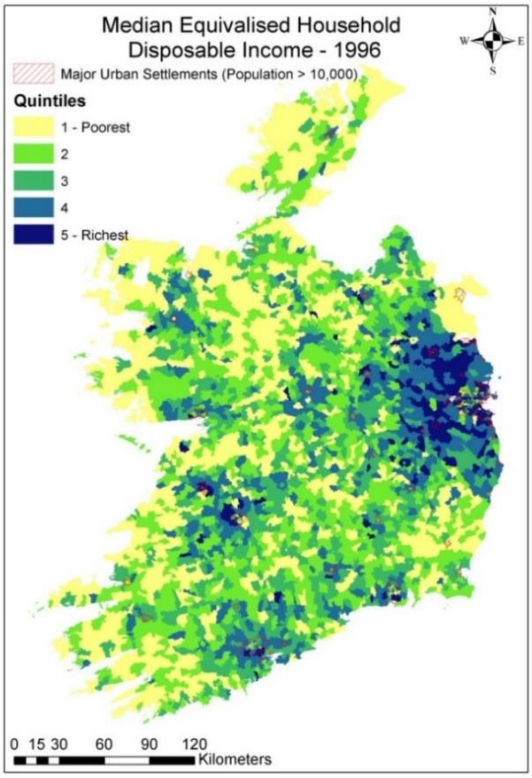
Source: Author Calculations

Table 3-3 shows a cross tab of the quintiles for the years 1996 and 2011. For Q5 it appears the majority of EDs in Q5 in 2011 have remained. As we are using the ED population totals from 2011, there appears to be more people living in the EDs in Q4 & Q5 now compared to 1996. This is supported by the higher population density (Table 3-6).

Our maps show the resulting spatial distribution maps of disposable income. Firstly, Figures 3-1 to 3-4 show the EDs divided into quintiles of median household equivalised disposable income.

[9] Quintile 5 (Q5) is the highest/richest, Quintile 1 (Q1) the lowest/poorest.

Figure 3-1: Disposable Income - 1996



Source: Author calculations

Figure 3-2: Disposable income - 2002

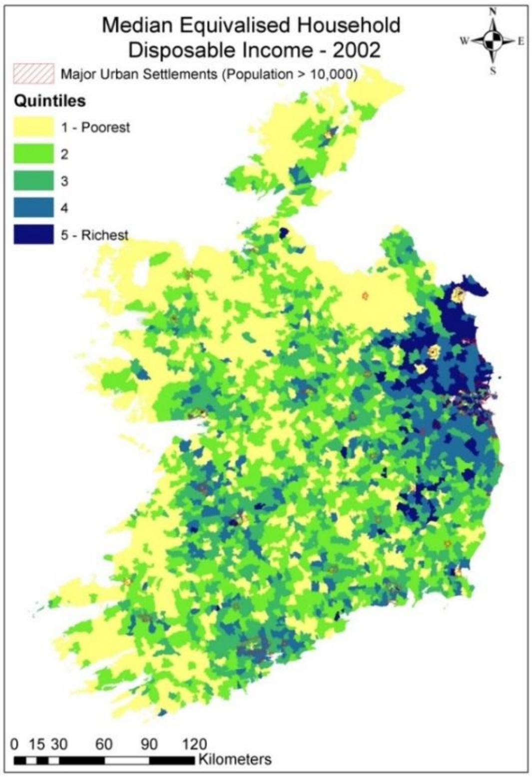
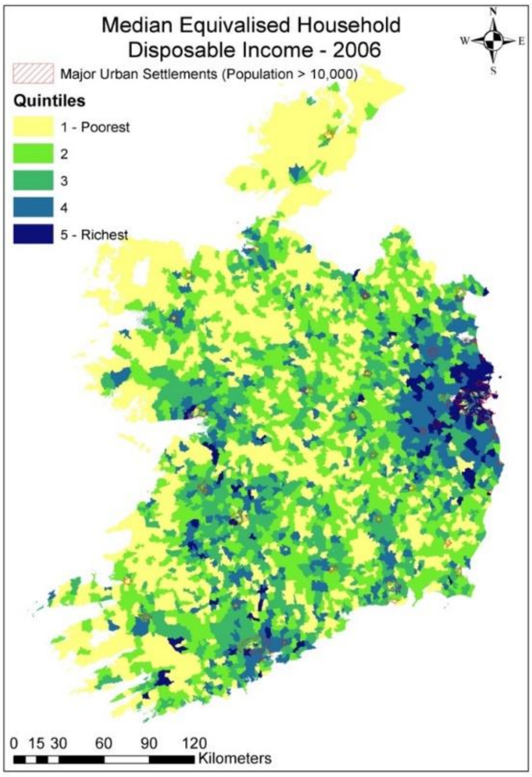
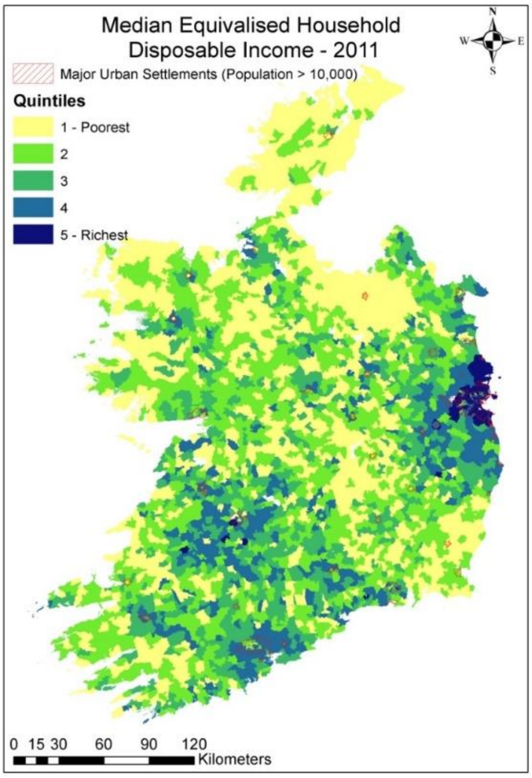


Figure 3-3: Disposable income - 2006



Source: Author calculations

Figure 3-4: Disposable income - 2011



There are some interesting results especially around the major urban settlements. If we look at the map for 1996 we can see that those in the commuter areas around Dublin are mostly in the top two quintiles. This covers quite a large area. The majority of areas with high levels of disposable income are centred on the major urban centres. This is what you would expect as these areas have better job opportunities, which in turn leads to higher salaries. There is a clear urban/rural divide. The EDs in the poorest quintile are for the most part a large distance from a major urban settlement, with the exception of county Louth.

As we move on to 2002 the GDA income landscape has changed. There is a clear shift towards the north of Dublin. High levels of income are also more concentrated around Dublin with even less EDs outside of the GDA in the top quintile. People seem to be willing to live in the suburbs and commuter counties around Dublin and commute into the city for employment. In 2006 the number of EDs outside of Dublin in the top quintile has reduced even further. Table 3-6 shows that population density in the top quintile is also increasing. This suggests Dublin City has become even more concentrated. It is attracting high levels of people in search of better opportunities. The south-west of the country has also seen an increase in the number in top quintile. While again the urban-rural divide is quite stark. Much of the centre and north of the map remains in the bottom quintiles. These areas are characterised by low population density, low levels of third level education and high unemployment. They also receive more in social benefits on average.

The final year 2011 has again seen a greater concentration in the GDA. A number of EDs in the commuter belt around Dublin have dropped out of the top quintile. We can also see that Cavan/Monaghan (North-Centre) is almost entirely in the bottom quintile. As mentioned earlier this area has the largest proportion of so called “ghost estates” and was particularly badly affected by the recession. Fortunes in the south-west of the country have continued to improve.

An examination of the breakdown of EDs in urban/rural as well as their quintile backs this up (Table 3-4). The more populated the settlement type the more likely an ED will belong to higher quintiles. Looking at those EDs in a rural area, 70% of all the population is in Q1 or Q2. The exception to the rule is Galway city where the majority are in Q3. A comparison between 1996 & 2011 shows that the gap between urban and rural has grown over time. There are now more people living in the urban areas in Q4 & Q5 and less people in Q4 & Q5 living in rural or small towns and villages.

Table 3-4: Income Quintile Movers by Geographical Area

	1996 Pop. share			2011 Pop. Share			TOTAL
	Q1 & Q2	Q3	Q4 & Q5	Q1 & Q2	Q3	Q4 & Q5	
Rural	63.0%	20.7%	16.4%	70.3%	19.1%	10.6%	100.0%
Village (200 – 1499)	51.2%	24.4%	24.4%	61.1%	25.4%	13.5%	100.0%
Town (1500 – 2999)	66.7%	22.1%	11.2%	68.7%	23.3%	8.0%	100.0%
Town (3000 – 4999)	42.9%	32.5%	24.6%	50.2%	40.9%	8.9%	100.0%
Town (5000 – 9999)	30.7%	32.3%	37.0%	51.2%	34.7%	14.1%	100.0%
Town (1000 +)	45.4%	20.8%	33.8%	33.8%	30.0%	36.2%	100.0%
Waterford *	38.5%	18.1%	43.5%	34.1%	30.7%	35.2%	100.0%
Galway	37.7%	14.7%	47.7%	40.4%	51.7%	7.9%	100.0%
Limerick	50.4%	9.0%	40.5%	39.5%	15.5%	45.0%	100.0%
Cork	34.1%	24.2%	41.8%	31.9%	13.8%	54.3%	100.0%
Dublin County	13.9%	16.1%	70.0%	3.1%	5.1%	91.8%	100.0%
Dublin City	15.9%	7.1%	76.9%	4.5%	2.0%	93.5%	100.0%

Source: Author Calculations

Large changes in Irish society have taken place during this time period. Table 3-5 shows the breakdown of working population by industry of employment. We consider the top quintile (Q5) and the bottom quintile (Q1) as well as the movers. There has been a large move away from manual industries such as agriculture, construction and manufacturing towards more professional industry sectors like commerce, public administration and professional services (e.g. education). Most interestingly the difference is over time rather than between quintiles which is negligible.

Table 3-5: Industry Share

	A	B	C	D	E	F	G	H
1996 Q1	12%	7%	18%	22%	5%	7%	18%	11%
2011 Q1	5%	5%	13%	29%	5%	11%	20%	12%
1996 Q5	10%	6%	17%	23%	5%	7%	19%	12%
2011 Q5	4%	5%	12%	31%	4%	12%	21%	11%
Mover								
Up 2Q +	4%	5%	13%	31%	5%	12%	20%	11%
Down 2Q +	5%	5%	12%	30%	4%	12%	20%	11%

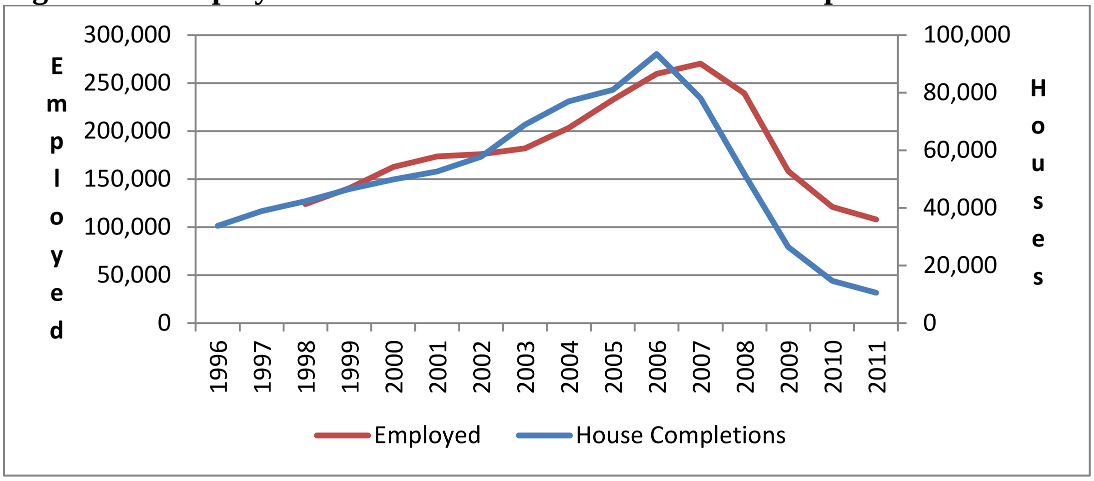
Source: Author Calculations.

Industry: A – Agriculture, B – Construction, C – Manufacturing, D – Commerce, E – Transport, F – Public Administration, G – Professional Services, H - Other (CSO, 2006).

The construction industry is particularly interesting as there was a large increase in employment in the industry followed by a sharp decline. In Forfás (2013) employment data in the construction sector was examined. In 2009 alone the number of unemployment construction workers increased by 190%, and construction workers accounted for 29% of all unemployment. Figure 3-5 shows the number of new house completions[10] broken down by census year. Put together with the employment figures in construction this goes towards explaining the reason behind the large numbers of construction workers unemployed in 2011. We can see this in Figure 3-5, as house completions begin to decrease in 2007, so too do employment figures in construction. There is however a lag of about 1 year before employment figures began to decrease rapidly.

[10] Figures are based upon the number of new connections to the electricity network. This excludes conversion of buildings into residential units. (The Department of the Environment, Community & Local Government).

Figure 3-5: Employment in Construction versus House Completions



Source: DECLG & CSO

It is obvious from the maps that there is a continuing concentration of activity around the GDA. Even within the GDA itself the number of EDs in the commuter belt in the top quintiles has continued to decrease over time while at the same time the population density of the EDs in Dublin city in the top quintile has increased. From Table 3-6 we see that employment income in Dublin is considerably higher compared to the rest of the country. The increase in the level of opportunities in the area has proven attractive.

Table 3-6: Quintile Characteristics

	1996		2011		Movers (quintiles)	
	Q1	Q5	Q1	Q5	Down 2 +	Up 2 +
Disposable income[11]	€5,869	€10,042	€15,615	€25,960	€18,178	€20,261
Youth Dependency	25.9%	23.2%	16.3%	10.4%	15.6%	14.9%
Old Age Dependency	15.8%	10.7%	16.5%	15.7%	15.7%	14.9%
University Educated	21.3%	35.6%	32.5%	47.1%	36.1%	37.6%
Employment Share	40.7%	48.6%	49.3%	56.4%	51.0%	52.0%
Unemployment share	8.9%	6.8%	12.3%	10.7%	11.8%	11.7%
Pop Density	490.6	2226.5	251.2	3379.9	597.5	1126.0
Age	36.34	34.35	42.07	42.73	41.85	41.64
Work Age Share	59.9%	67.8%	68.2%	74.8%	69.8%	71.2%

Source: Author calculations.

Table 3-6 shows the average values for Q1 & Q5 for the years 1996 and 2011. Population density in the top quintile has increased between the two years. There has been a convergence of people into the urban areas as they seek better opportunities.

[11] Median Equivalised Household Disposable Income

Levels of education have increased over time; even those in the bottom quintile have seen the percentage of adults with third level education increase. Employment is also higher in 2011, as is the share of people of working age. Unemployment however is also higher in 2011 as a result of the recession.

Youth dependency has decreased while at the same time old age dependency has increased. This would suggest an ageing population. The top quintile is made up of a high proportion of older people in 2011 compared to 1996 which would suggest that those over the age of 65 were less affected by the recession. Most of the analysis conducted is cross-sectional between areas. Table 3-7 shows the Theil index I_2 (Shorrocks, 1982). The Theil index decomposes inequality into two components between and within variability. We can see that much of the variability is occurring within rather than between EDs. Although our maps show that there is a changing landscape across Ireland much of this change is occurring within EDs rather than between them. An examination of the tabulations of income by area shows that to be the case. Within an area we cannot say definitively whether an ED has more individuals in one particular quintile on the income distribution.

Table 3-7: I_2 index - Disposable Income by Year

Disposable income	1996	2002	2006	2011
I_2	1	1	1	1
Between	0.06	0.07	0.02	0.04
Within	0.94	0.93	0.98	0.96

Source: Author Calculations

3.6 Conclusion

From our results we have seen an increase in concentration in and around Dublin City. This has largely been to the detriment of the rest of the country. Urban areas are vastly outperforming rural areas. The statistics of the areas in the bottom quintile which are largely rural are not promising. These areas are characterised by high levels of unemployment, low income and low levels of third level education. Equally there may be non-monetary reasons why individuals are choosing to live in these areas, such as better amenities and a better lifestyle/environment.

What our results have shown is that current policy is failing. Government has failed to control the concentration of economic activity around the GDA. The trends are worrying and have already led to a housing crisis particularly in the GDA. This crisis was inevitable given the increasing wages and property prices in these areas. Our Theil index results show the high levels of inequality within rather than between EDs. Within an ED there are vast differences in income. Dublin has proven attractive to those with high levels of education who demand a higher wage. This has led to people converging on Dublin hence the increasing population density over time. Policy should look at addressing this issue by improving job opportunities in medium to small sized towns. This could be achieved by improving the infrastructure in these areas to bring them in line with the facilities etc. available in a major urban centre such as Dublin.

Policy can go some way towards improving the economic performance of a region. Removing the barriers around mobility of labour is one option (Marston, 1985, Carlsen, 2000, Armstrong and Taylor, 2000). Attractive living conditions; good services, high wages; have led to permanent differences in the wage and unemployment rate. It is difficult for income to increase in an area of high unemployment due to the excess in labour supply. The districts with the lowest incomes also tend to be the districts with the highest levels of unemployment. There is a spatial concentration of those most at risk of poverty. Increased investment in public housing in areas where there are better opportunities is one method of supporting the movement of people out of high poverty areas. Government subsidies can make it affordable for them to live in more prosperous regions and areas.

Centrifugal forces include high rents, commuting which then leads to congestion and supply of immobile factors (Fujita *et al*., 2001). Currently the Greater Dublin Area (GDA) is facing a crisis in this regard (increasing rents, congestion issues, and low property supply). The effect of these forces on disposable income warrants further investigation, for example, quantifying how much an average worker is spending each year on commuting costs and on renting a property.

Using a spatial Microsimulation approach allows us to examine incomes at an individual and household level. This has enabled us to create an income distribution at a spatial level by firstly calculating the median equivalised household disposable income of an ED and then dividing this into quintiles taking into account the population of the EDs. Examining by urban/rural and over time we have observed the changing landscape in Ireland, a move of workers/people towards the major urban centres, the increase in wealth of these areas, the vast change in the breakdown of industry of employment and finally the change in the socio economic characteristics of the quintile groups.

This analysis includes an economically diverse period, represented by strong economic growth, a property bubble and subsequent collapse and recessionary period. Examining at the small area level has allowed us to track an area's economic status over time and also the socio-economic and socio-demographic characteristics of its residents. Our analysis shows the increasing regional imbalance between urban and rural areas. This gap has increased during the time period examined in this paper. Next steps involve examining ways in which this regional imbalance can be corrected.

Chapter 4. Effect of Housing on the Distribution of Welfare[12]

4.1 Abstract

The measure of a household's wealth should include not only monetary components but also non-monetary components and in-kind benefits such as imputed rent. In this paper the impact of net imputed rent on the distribution of income is examined in a spatial context. Two aspects of housing make it interesting; namely its costs and benefits. Housing wealth can provide a stream of consumption value. This will come in the form of imputed rent. Imputed rent is the rent an owner can expect to receive were the house on the rental market. We examine the spatial impact of net imputed rent, mortgage payments, private rent, public rent (social housing schemes) and annuity values on the distribution of disposable income from SMILE for the year 2011. 2011 is examined as it is the latest Census year for which detailed spatial micro data is available. We measure rental values at a detailed spatial scale (Electoral Division) adopting the kriging methodology (Brunsdon and Comber, 2015). To measure mortgage values, missing data analysis is employed to match various data sources (Enders, 2010). The created data is merged into the SMILE population dataset to examine the impact of housing on the spatial distribution of disposable income at a small area level. Our results show that housing decreases the income share of those at the top and bottom of the income distribution. The income of the elderly is also greatly increased.

4.2 Introduction

Assets such as consumer durables provide a stream of benefits (Barr, 1998). This stream of benefits will increase a households potential to consume (Atkinson, 1983). A comprehensive measure of welfare will therefore account for the consumption value derived from consumer durables such as housing (Smeeding and Weinberg, 2001). The value of these benefits and the costs associated with purchasing the asset will depend on area. House prices are hedonic therefore any measure of the costs and benefits from housing should reflect this (Rosen, 1974). In this paper the impact of net housing costs and benefits on the spatial distribution of income is examined.

The measure of a households wealth should include not only monetary components but also non-monetary components and in-kind benefits such as imputed rent (Frick and

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Grabka, 2003, Frick et al., 2007). Two aspects of housing make it interesting, namely its costs and its benefits. The costs in the form of rent, mortgage payments or house purchase and benefits; imputed rent and annuity value/reverse mortgage (Nakajima and Telyukova, 2014). Being an owner occupier does not provide a rental income, however it saves the owner from having to pay market rent (Atkinson, 1983). The impact of these costs and benefits on the spatial distribution of welfare is then assessed.

There is an argument that income from the production of household service for own consumption should be included into the calculation of household income. This is particularly applicable when a large proportion of the population produce their own household services (OECD, 2013a). Other streams of consumption come from household consumer durables and household services such as cooking. We do not consider income for household services here as there is a lack of data and difficulty in their accurate measurement. We do however measure income from consumer durables such as housing in the form of imputed rent.

Net imputed rent will consist of the gross imputed rent less any expenditure on maintenance and mortgage interest paid (Frick et al., 2007). For gross imputed rent the market rent for a similar type dwelling should be used (UN, 1977). The Canberra Group (UN, 2011) set out guidelines on how to measure household income and what components should be included. It outlines various monetary and in-kind gains which includes property income from net imputed rent, which should be included in the calculation of household income. Imputed rent and annuity values are now included in the United Nations system of national accounts 2008 (UN, 2008) while the CSO contains a net imputed rent measure in its national accounts (CSO, 2011).

A right to shelter and or housing is one of the basic human requirements set out in the Universal Declaration of Human Rights and International Covenant on Economic, Social and Cultural Rights (UN, 1966). Despite this, individuals struggle with providing their own dwelling. In such cases the state fills the void by providing the housing in-kind benefit. Paulus et al. (2010) make the point this public transfer in-kind would have to be paid out of disposable income were it not provided publicly by the state. In order to make reasonable comparisons between inequality rates of two countries such in-kind benefits (e.g. education, health and housing provision) should be considered whether they are publicly provided or provided out of disposable income. Failure to do so may lead to invalid conclusions and comparisons (Smeeding and Weinberg, 2001). The

Canberra group handbook (UN, 2011) and the OECD Framework (OECD, 2013a) have gone some way towards creating a standardised cross country measure of household income.

When considering and measuring net imputed rent it is also important to consider the underlying structures that exist in a country (Frick and Grabka, 2003, Norris and Winston, 2012). Low-income affordable housing, tax breaks such as relief on capital gains, mortgage interest relief and construction subsidies are all forms of government transfers from which households benefit. The non-taxation of imputed rent should be accompanied by no mortgage interest relief. It is widely acknowledged that such a tax relief has minimal impact on ownership percentage (Hendershott and White, 2000) and is inequitable towards renters (Bourassa and Grigsby, 2000). Mortgage interest tax relief is a regressive tax with higher income groups disproportionally capturing most of the gains (Matsaganis and Flevotomou, 2007).

There is a greater need to understand housing benefits within each country (Fahey and Maître, 2004). Before cross-country comparisons can be made detailed spatial micro data is required (Meen, 2012). We must understand in detail the intrinsic nature of the housing landscape. It is clear from research that institutional differences in relation to housing tenure, regulations, taxation, the welfare state and the quality, quantity and prices of dwellings lead to different data results across counties. In a country such as Ireland, which can be defined as having a liberal welfare state regime (Kemeny, 2002), we can expect rent prices and imputed rent to be higher compared to other countries where the market has less importance (Juntto and Reijo, 2010).

There are several economic advantages to owner occupation. Owner occupiers benefit from not paying private market rent. In many cases, monthly mortgage payments are lower compared to the rent for a similar dwelling (Lyons, 2017a). Owner occupiers may also use purchasing the property as a form of investment rather than investing in financial services (Frick and Grabka, 2003). Later in the life-cycle they can benefit from this investment in the form of an annuity or reverse mortgage. Investment firms offer a housing annuity value. This is where they purchase the house from the owner occupier and will provide them with a monthly payment until death (Nakajima and Telyukova, 2014). This monthly payment will depend on the age of the owner occupier. In that sense housing wealth provides a stream of consumption value by allowing them to consume the equity while still being able to live in the house (Mayer and Simons, 1994).

Including imputed rent reduces measured levels of inequality and poverty particularly for those who own their house outright and those in heavily subsided public housing with the elderly benefiting the most (Frick et al., 2010). Indeed a number of studies have also found that by including wealth indicators such as imputed rent, the measured living standards for the elderly is increased (Frick and Headey, 2009, Callan and Keane, 2009, Pellegrino et al., 2011). However the introduction of a tax on imputed rent may not necessarily be progressive especially in countries where the elderly have lower cash incomes than other groups (Figari et al., 2016, Pellegrino et al., 2011, Yates, 1994). Net imputed rent is proven to decrease inequality and reduce poverty especially amongst the elderly (Törmälehto and Sauli, 2013). The benefits of imputed rent to social renters are also found to be substantial decreasing poverty rates as much as 10% (Grabka and Verbist, 2015). Overall imputed rent can have a equalising effect on the income distribution (Saunders and Siminski, 2005, Fessler et al., 2016).

Policy Context

The financial crisis in Ireland has left behind a housing system that is spatially and inherently unequal; high levels of negative equity exist in the commuter belts (Hearne et al., 2014). In Ireland, there has been much criticism of the bias surrounding owner occupation in (OECD, 2006) with recommendations for the introduction of a property tax (Daly et al., 2009). There has been an incentivisation of home ownership particularly in rural areas (Gkartzios and Shucksmith, 2015). One of the results of the crisis are the so called “ghost estates” (residential units unfinished or abandoned) (Kitchin *et al*., 2010). Census data 2011 shows that there was an oversupply of housing, with approximately 15% vacancy rates (SAPS, 2011). This problem is especially bad in the former Upper Shannon Rural Renewal Scheme area, where a building tax incentive scheme existed between 1999 and 2008. The area now contains 18% of all “ghost estates” (Kitchin et al., 2014).

The housing sector is one asset most widely taxed by policy makers. In an Irish context the Income Tax Act 1967 taxed income from the letting of a property or the imputed rent to the owner occupier. This tax was later abolished in 1969. A domestic rates system had been in place in Ireland since the mid-19th century. These rates were used to fund local government and were based on the valuation of the property. This amount however was calculated based on the level of funding the local government required for its annual budget. The system was abolished in 1978 amid political controversy (Daly et al., 2009). In 2013 a local property tax (LPT) was introduced (Walsh, 2013). The LPT is a self-assessed tax and it is the responsibility of the owner to select the correct band in which they believe their property belongs to. The LPT website contains some guidance in relation to this; however the bands are quite wide with little information given in relation to housing characteristics. This tax however can capture some of the in-kind benefits from owner occupation, however as the tax is on all residential properties those renting privately and those with a mortgage are also impacted. Callan et al. (2010) recommended an income exemption were a property tax introduced however the current tax does not discriminate based on income

In this paper, we examine the spatial impact of net imputed rent, mortgage payments, private rent, public rent (social housing schemes) and reverse mortgage values on the spatial distribution of disposable income from SMILE for the year 2011. 2011 is examined as it is the latest Census year for which detailed spatial micro data is available. We measure rental values at a detailed spatial scale adopting the kriging methodology (Brunsdon and Comber, 2015). To measure mortgage values, missing data analysis is employed to match various data sources (Enders, 2010). A spatial model approach to imputed rent have been limited due to a lack of spatial information in surveys (Balcázar et al., 2014). Adding a housing component into the SMILE population dataset overcomes this issue and allows us to examine the impact of housing on the spatial distribution of welfare.

4.3 Methodology

In this paper a spatial microsimulation approach is used to overcome the lack of income data at a spatial scale. Census data typically has a spatial component but no income information whereas surveys typically have individual incomes but no spatial information. Spatial microsimulation presents us with information on household income and housing tenure information at a spatially disaggregated scale. Using spatial models to estimate rents and property prices at a detailed spatial scale and linking this data to the simulated population dataset, allows us to examine imputed rent at a detailed spatial scale.

The spatial distribution of welfare used in this paper comes from the SMILE model (O'Donoghue et al., 2013a). Disposable income is used as a proxy for welfare.

Disposable income will consist of income generated from employment, non-work income such as income generated from investments, social benefits and then less any taxes.

$$Y_i = w_i + f_i + b_i - t_i$$

Where Y_i is an individual's total personal income, w_i is employment income, f_i is non-employment income such as investments, b_i are social benefits and t_i any taxes (includes tax on employment income, non-employment income and social benefits).

Spatial Microsimulation

To generate a spatial distribution of income we require income data at a meaningful scale. Spatial Microsimulation has a number of advantages over published aggregate totals. It can be linked to other datasets, can be spatially disaggregated or aggregated, data is stored as lists and the models developed can be updated (Ballas et al., 2006b). Normally there is a lack of income data contained in small area census data; however there is detailed additional spatial information. The opposite is true of survey data; it contains data on income but has poor spatial detail. Spatial microsimulation helps in overcoming these problems. This paper uses the output from the SMILE model. SMILE is a static microsimulation model (Morrissey *et al*., 2013) which has been developed by the Rural Economic Development Programme, Teagasc and the School of Geography at the University of Leeds (Morrissey *et al*., 2008). The SMILE model aids in creating a spatially disaggregated population micro-dataset with detailed income and spatial information. It does this by matching overlapping variables between the census and survey datasets (Morrissey *et al*., 2008). SMILE uses quota sampling (QS), which is a probabilistic reweighting method (Farrell et al., 2012b). It works by firstly randomly ordering the micro data, it then samples from the micro data until the quotas - which are set by the constraint variables from the census - are filled. This data is then calibrated to ensure that the data is representative. Once calibration has been performed, SMILE presents us with a dataset which contains market income as well as other demographic information at the electoral division (ED) level for each individual in the population.

Tax-Benefit System

This micro-dataset created by SMILE contains socio-economic, demographic, labour force and income information at the individual and household level which is also spatially referenced. For an in-depth discussion on the SMILE model see (Morrissey and O'Donoghue, 2013, O'Donoghue et al., 2013a). The SMILE model also takes into account the complex nature of the tax-benefit system. Income is modelled net of taxes and benefits. In order to do so a static microsimulation model of the Irish tax-benefit system was developed. In Ireland a number of similar models have been developed such as the SWITCH model (Callan et al., 1996b) as part of a European tax-benefit model (O'Donoghue, 1998). A simplified Tax-Benefit microsimulation model was programmed in Stata to model the spatial distribution of income net of taxes and benefits. This model is consistent with other publicly available models such as EUROMOD. SWITCH is not publicly available. The tax-benefit system is simulated for each of the census years. For a technical overview of the process please refer to (O'Donoghue et al., 2013a). This component of the SMILE model is important as the distribution of our disposable income measure relies upon, not only the distribution.

Equivalence Scales

Typically income is adjusted to take account of the varying composition of households. Equivalence scales are often used to overcome this issue (Atkinson, 1983). Income is measured at an equivalence scale to take account of the need of the household. Although there are many scales (OECD, 2014b), we use the national equivalence scale as this is the one which is widely used by the CSO in its SILC reports. This scale gives a weighting of 1 to the first adult in the household and 0.66 to each subsequent adult (>14 years). Children (<14 years) are each assigned a weighting of 0.33. These weightings are totalled to calculate the equivalised size of the household (CSO, 2014b). The equivalised household disposable income is then calculated for every household in the country.

Housing Component

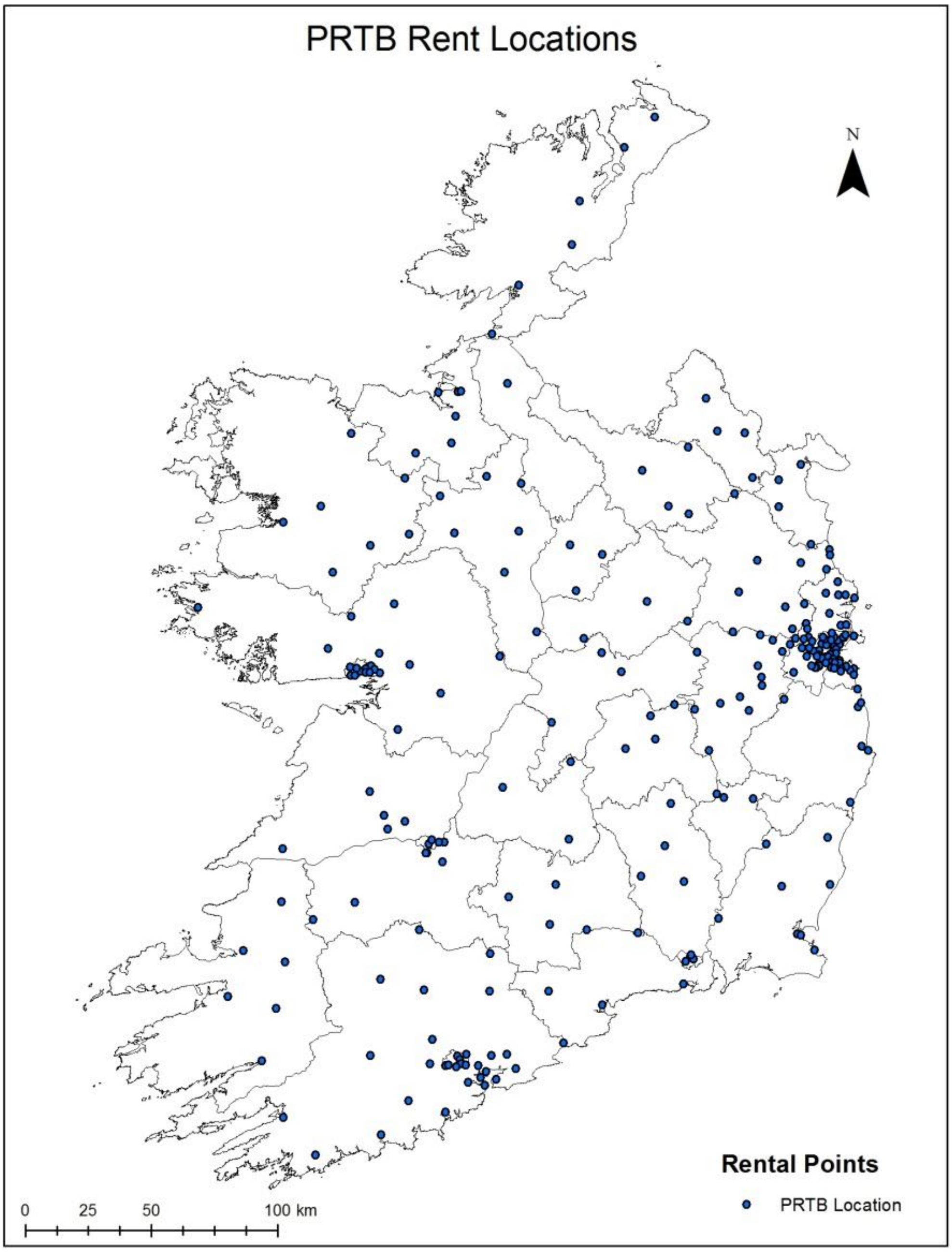
The spatial distribution of disposable income from SMILE is used as the base measure. Various house components are then added where they are relevant; private rent, public rent (social housing), mortgage costs, imputed rent and annuity value. This paper takes a cross-sectional examination at the year 2011, we focus on 2011 as this is the latest year for which SMILE model income data is available. In addition to calculating imputed rent, we also examine the impact of imputed rent in addition to housing wealth in the form of annuity values at a spatial scale.

Kriging

There are a number of methodologies which can be used to estimate imputed rent (see Balcazar et al. (2014)). A thorough literature review proved inconclusive as to what the best method for measuring imputed rent is, all having advantages and disadvantages. Spatial models capture the fact that the residuals produced by hedonic house price equations are often spatially correlated (Balcázar et al., 2017). Although spatially detailed house information is available, previous studies have been constrained by a lack of spatial information in survey data. Using a spatial microsimulation approach has enabled us to overcome this problem. A spatial model is used to estimate house prices and rental prices at a detailed spatial scale. In this paper we use the kriging methodology. The kriging methodology employed is used to interpolate or smooth spatial data (Diggle et al., 1998). It is often used in spatial statistics (Cressie, 1990) and has been used to estimate house prices (Montero and Larraz, 2010). Kriging operates on best linear unbiased prediction (BLUP) (Goldberger, 1962) while at the same time taking into account spatially correlated data. It is based on Tobler's Law that everything is related to everything else but nearer things are more related to each other (Tobler, 1970). It takes account of this by placing a greater weight on observations which are closer to each other.

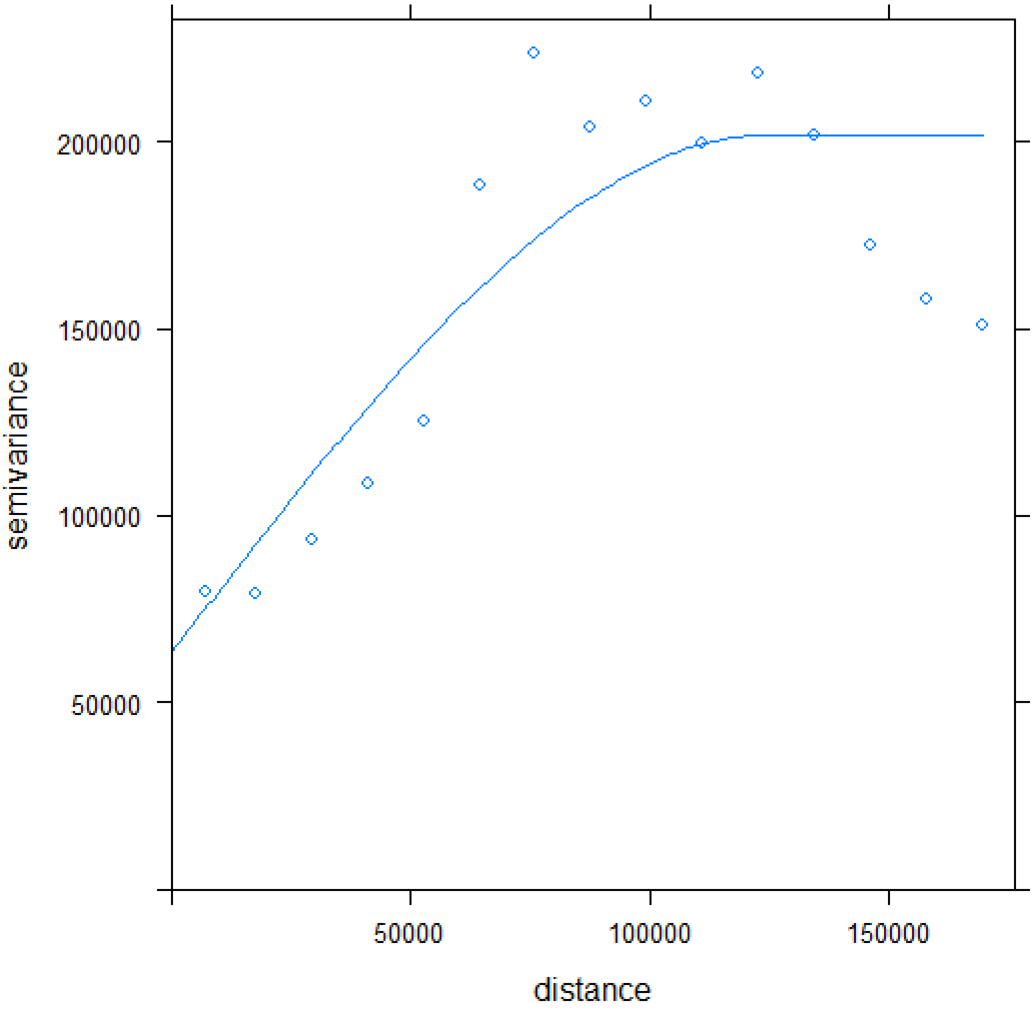
Kriging assumes we can estimate the variance-covariance matrix as a function of distance only. When applied, kriging creates a smooth interpolation surface between the points which are measured. The variance-covariance matrix is estimated by firstly computing a variogram (Pace et al., 1998). The pair-wise squared differences among all errors, are plotted against the distance between the pair points (Bailey and Gatrell, 1995). We can assume there is a boundary where the distance is greatest and at which the value of one point is related to the value of another point (Hoshino and Kuriyama, 2010). As distance increases the covariance converges towards zero. The points beyond this range will have zero impact on the points inside the range or boundary. In kriging a greater weight is given to points which are closer in distance to the dependant (Dubin et al., 1999). Kriging is often used to estimate real estate values (Hoshino and Kuriyama, 2010, Pace et al., 1998, Dubin et al., 1999, Dubin, 1992, Basu and Thibodeau, 1998). The variogram in the model takes account of this by placing more weight on the values of the objects which are closer. The level of weight decreases at an increasing rate until objects are at a distance where there is no effect on the value estimated.

Figure 4-1: PRTB Rental Locations Geocoded



The rental points are plotted using the software programme R. Using the kriging methodology, we firstly estimate the variogram (Figure 4-2). This variogram is then fitted to the data to determine the range, sill and nugget. Beyond a distance of 76.3 km rental points no longer have an effect on the interpolated value. A rental value for each of the 3,440 Electoral Divisions is estimated. We use the centroid point of the ED to represent it. The output from the kriging methodology is an estimation of private rent for an area broken down by property type and number of bedrooms.

Figure 4-2: Estimated Variogram from the kriging Methodology (Distance in metres)



Social Housing Rent

Once a rental value has been estimated for each ED broken down by number of bedrooms, this value is then used in the model to represent private rental and imputed rent prices. Social housing rents are calculated using the rent supplement values from the Department of Social Protection. We use the max value in each band for the area in question and subtract this from our estimated rental value. This difference represents the housing cost to those in social housing. The net imputed rent for those in social housing will consist of the private rent the property can achieve on the private rental market less any costs; where the costs are rent for property on the rental market less rent supplement payment.

Data imputation

To be able calculate mortgage repayment cost we require an estimate of house prices going back twenty-five years from 2011. The Department of Housing provides us with average house price figures over the period 1971-2016. This however is at an aggregate spatial scale (provincial cities and national). It also only lists values for a three-bedroom semi-detached property.

To overcome this problem average list prices from the property website Daft.ie are used. The Daft data provides us with average list prices broken down by Local Authority (34 divisions) with extra divisions for Dublin. It also breaks down prices by number of bedrooms. Property prices are then modelled based on the relationship between the three-bedroom property in the Daft data and the Dept. of Housing Data.

$$Prop_{cit} = \left[\frac{Rent_{cit}}{Med\_Rent_{cit}}\right] * \left\{Dept_{ct} * \left[1 + \frac{Daft_{cit} - Daft_{c3t}}{Daft_{c3t}}\right] * \left[\frac{Daft_{c3t}}{Dept_{c3t}}\right]\right\}$$

Where c is location, i is number of bedrooms and t is the year. Prop is the value of the property, Rent is the ED rental value, Med_Rent is the median county rental value, Dept is the Department of Housing property value and Daft is the Daft.ie property list price. By using our kriging rental values, we can estimate the pattern in housing value across a county. Taking this approach will provide a smoother distribution of house prices across space.

Mortgage

Unfortunately the spatial microsimulation process does not present us with rich mortgage information, other than whether or not an individual has a mortgage. As this is a hypothetical model, we can make a number of assumptions around the other mortgage details we require such as year mortgage was drawn down, mortgage type, interest rate and Loan-to-value (LTV). Using data from the Central Bank of Ireland (CBI) we discover that 28 is the average age at which people typically drawdown a mortgage. We also discover that 78.7% is the average LTV percentage (RTÉ, 2016). Unfortunately this average value data is not available going back through time. During the year of concern in this paper 2011, the difference in the interest rate across mortgage types (tracker, variable and fixed rate) was minimal, we therefore use the same interest rate across all mortgage types. This also overcomes the lack of detail in the SMILE model on mortgage type and level of interest.

Using their age, we assume the drawdown of their mortgage occurred when they were 28. From this we can establish in what year they purchased the house and using the house price for that year for the ED in which they are living. Using the LTV rate of 78.7% we calculate how much of a mortgage they required. By using the interest rate for 2011 it is possible to estimate the mortgage repayments and interest repayments. These repayments represent another cost against net imputed rent.

Annuity Value

An annuity value also called a reverse mortgage, allows owner occupiers to use their home equity to borrow without the need to move out or sell the house. The annuity provides the homeowner with regular payments. The loan is then repaid with interest upon the homeowner's death or if they decide to sell. Unlike taking out a mortgage on a property, the homeowner is not required to make interest or principal payments. It allows the homeowner to drawdown from the equity they have built up in the asset and is a way of supplementing income particularly amongst the elderly. The typical annuity the borrower receives depends upon a number of factors; the borrower's age and life expectancy, the amount of equity in the home, the expected level of house price appreciation and the interest rate on the loan. The borrower will then receive payments for life until death or if the house is sold (Mayer and Simons, 1994). It may be the case that the value of the loan exceeds the value of the property at the time of sale which is a significant risk for the lender (Mitchell and Piggott, 2004). However there is a strong correlation between people who take out an annuity and home departures, which suggests many do not see it through until death (Davidoff and Welke, 2004). Despite the benefits of annuity values in decreasing poverty amongst the elderly (Kutty, 1998, Mayer and Simons, 1994), the demand for annuities remains low and the reasons for this remain not well understood (Cocco and Lopes, 2014). Venti and Wise (1991) estimate that housing equity represents as much as 80% of the wealth of elderly households. In a sense many are "cash-poor and house-rich" (Costa-Font et al., 2010). It is therefore puzzling as to why there is not a greater demand for annuities. Although annuities are typically only given to those aged 62 and over (Mayer and Simons, 1994). In this model, we do not have an age cut-off as hypothetically if an individual owns their home outright they have a choice of taking out a housing annuity. This should not prove problematic to the lender as they can consider the uncertainty around length-of-life when calculating payments. An age-dependant discount rate with later years discounted at an increasing rate we can take account of age (Fratantoni, 1999). We therefore do not ignore the demand for housing annuities among younger age groups (Rasmussen et al., 1997). As you would expect those in older age categories will typically receive higher payments as their payments are expected to last over a shorter time.

Once all housing information has been modelled at a detailed spatial scale, we now have an estimate value for private rent, public rent (social housing), imputed rent, mortgage repayments and annuity value. When we combine the relevant values together for the household we get the overall net housing benefit or cost. This value is then factored into the calculation of disposable income to estimate the effect of housing on the spatial distribution of disposable income.

4.4 Data

Due to the complexity in calculating detailed spatial information a number of data sources were utilised. Firstly a measure of income at a small area was required; secondly the various housing costs and benefits are calculated, including private rental values, social housing values and house price values.

Income Data

As mentioned previously the SMILE model contains survey and census data in simulating incomes. For the year 2011 EU-SILC survey data is used. EU-SILC has been collected in Ireland since 2003 with a typical sample size of 5,000-6,000. It collects data on income, health, labour and education to name a few. Using EU-SILC data allows us to overcome the problem of a lack of data on income in Census data such as the Small Area Population Statistics (SAPS). SAPS are census data which contains population totals broken down by themes[13] at the ED level. Since 2011 SAPS are available at a new, more spatially disaggregated unit, Small Areas (SA)[14]. We however will only consider the ED level as there are issues in using spatial microsimulation at the SA level.

The advantage of using the data from SMILE over Census data only, is the extra information on income. Existing income data from the CSO is aggregated to county level. Although useful, it gives little indication as to how the distribution of income

13 Themes include sex, occupation, and industry. All are totals at the ED level.

14 SAPS 2011 contains data on 18,488 Small Areas. There were 3,409 EDs that same year.

within each county varies spatially. The data from SMILE makes it possible to examine at a local level, ED in this case, which areas moved up and down the income distribution over time. It then allows us to identify the characteristics and drivers of these areas. Any reoccurring characteristics or drivers which emerge may prove useful in identifying areas most in need of state support and government resources.

Rental Data

Our rental data comes from the Residential Tenancies Board (PRTB, 2011) rental index. Under the Residential Tenancies Act (2004) landlords are legally obligated to register with the PRTB. The PRTB rental index should therefore give us values based on population data (assuming all landlords are compliant). The dataset is compiled by the ESRI, began in 2007. It is based upon the RTB's register (which contains 284,038 registered landlord properties) of tenancies, it therefore based upon actual rents being paid. The database is the largest in rental index in Ireland and is populated with information on actual/agreed rent, location, six categories of dwelling types, accommodation size and number of occupants and tenancy length.

The rental points used in kriging were geocoded using An Post's Geodirectory database. The address points were at an unknown geographic unit so were geocoded manually based on the location detail provided. Using ArcGIS software all properties in the Geodirectory was plotted. Each address from the PRTB data was then used in a search which highlighted every address where there was a match. Where possible the centre point of a cluster of buildings was chosen. In towns and villages, the address "main street", "church street" or "square" was chosen as this represents the centre point of the area. In some cases (especially in rural areas), some variables contained missing data. Where this occurred data was imputed using the ratio of property type to property type from another area.

It is estimated using hedonic regression which is based on the presumption that goods are tied packages of characteristics with observed market prices linked to those characteristics (Rosen, 1974). For the RTB index the characteristics used are dwelling size, dwelling type, location and other characteristics. For an in depth discussion see (ESRI, 2013).

For the year 2011 the published database shows there were 393 rental data locations, with a greater number of points in the main urban centres. Each point represents the average rent received in a catchment area and contains data broken down by property type and number of bedrooms.

Table 4-1: PRTB Housing Breakdown

Property Type	Number of Rooms
All property types	1, 2, 3, 4, 5
Apartment	1, 2, 3, 4, 5
Semi-detached	1, 2, 3, 4, 5
Detached	1, 2, 3, 4, 5
Terrace	1, 2, 3, 4, 5

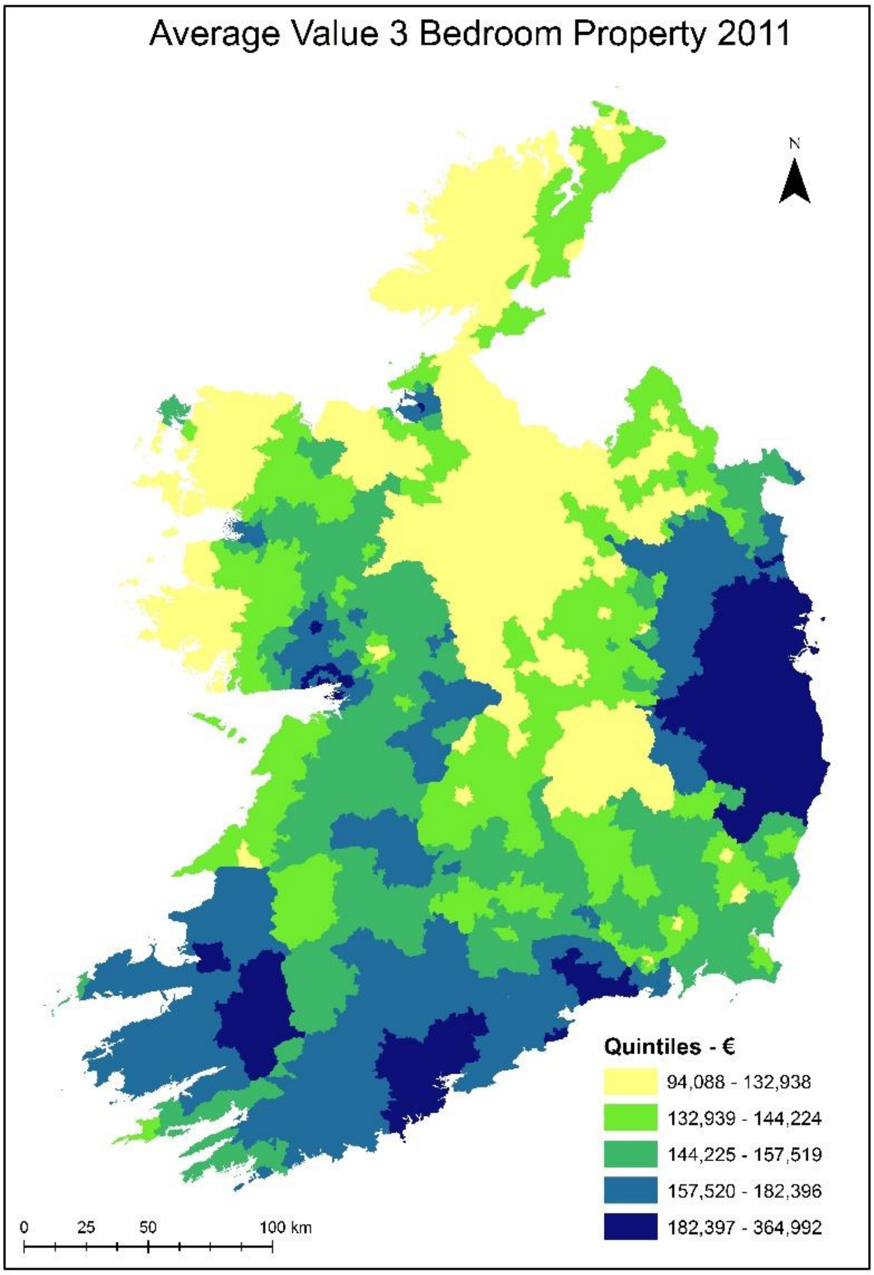
House Prices

The Department of Housing gather average house price data based on mortgage approval data (Department of Housing, 2016). The data is presented as a simple average for a three-bedroom semi-detached house. Although the data has information on actual house sales it lacks spatial detail. Values are broken down by year (1971 – 2016) and by several categories; national, Dublin, Cork, Galway, Limerick, Waterford and other areas. We use the averages for new houses which represents a three-bedroom semi-detached house. In tandem with this dataset data from the Daft.ie (Lyons, 2017b) is used which contains more detailed spatial information. The report contains average house list prices broken down by Local Authority[15] and number of bedrooms (1-5).

Combining both data sources together allows us to overcome the lack of spatial detail in the Department of Housing data and the lack of actual sales prices in the Daft.ie data.

[15] Prices are broken down by Local Authority outside of Dublin. Inside Dublin the Local Authority of Dublin City is split into north and south city. Also Tipperary is not broken into its two local authorities of north and south.

Figure 4-3: Average Price of 3 Bedroom Property in 2011



Mortgage Data

Given the requirement for interest rate data from 1985 to 2011, finding a dataset which would cover this time and at the same time be consistent was going to be difficult. Owing to the introduction of the Euro in 1999, some data sources only go back as far as then. We would have to be confident around having consistent definitions before amalgamating two datasets. There was also the increased complexity of having different interest rates based on the mortgage type; tracker, variable and fixed. To overcome this problem we assume all mortgages are variable rate mortgages and take the ECB variable rate interest rate for 2011 of 1.25% (ECB, 2016). In any case, we do not have detailed individual information on the type of mortgage an individual has, only that they have a mortgage or not.

Reverse Mortgage

The Reverse Mortgage is the annuity an individual who owns their house outright can receive when they sell their house to an investment firm. The amount of annuity they receive is highly dependent on age. We calculate the reverse mortgage annuity by dividing the current market value of the house by the number of adults in the household. This attributes a proportion of the value to each adult. We then apply a formula which calculates the annuity for everyone who has a proportion of the assets value. The older the individual the more of an annuity they will receive.

4.5 Verification

Table 4-2: Variable Definitions

Variable	Definition
Disposable Income	Equivalised Household Disposable Income
Housing Costs	Private Rent Costs + Social Housing Costs + Mortgage Costs
Imputed Rent	Imputed Rent Household Receives
Net Imputed Rent	Imputed Rent - Housing Costs
Reverse Mortgage	Must own house outright (no mortgage)
Net Housing	Imputed Rent - Housing Costs + Reverse Mortgage

Table 4-2 shows the definitions of the various measures used to estimate the impact of housing on inequality and income. Each measure has been equivalised so a more accurate comparison to equivalised disposable income can be made.

From Table 4-3 we can see various income and rent measures broken down by age group. While the elderly have low levels of income their high levels of imputed rent and annuity compensates for that. After taking account of housing costs and benefits their age group moves from having the lowest levels of income to having the highest. Due to the younger age categories not owning a property or still having a mortgage, they cannot benefit from having an annuity or high imputed rents.

Table 4-3: Age Group Housing Income Streams

Age Group	Median Employment Income	Median Equivalised Income	Net imputed Rent	Median Annuity	% Annuity Zero	Median Equivalised Income (including housing)
15-35	€13,359	€20,165	€0	€0	69.0%	€22,126
36-50	€21,178	€19,978	€1,359	€3,006	29.1%	€25,459
51-65	€16,266	€19,124	€5,066	€5,846	14.2%	€30,590
65+	€13,942	€16,612	€5,103	€12,060	4.3%	€38,118
15-65	€16,314	€19,686	€1,929	€2,485	39.0%	€26,004

Table 4-4 illustrates this more clearly, as age increases it becomes less lively an individual has a mortgage or is renting. In the 65+ age category 97.7% are owner occupiers and only 0.8% have a mortgage. By owning their own home without a mortgage, they can benefit from imputed rent and consumption value in the form of a reverse mortgage. The high numbers in the 15-35 age category is a concern. By paying rent they are at more of a disadvantage as they are not paying into an asset and secondly not benefiting from the in-kind benefits which that brings.

Table 4-4: House Tenure by Age Group

Age Group	Has Mortgage	Private Renting	Social Housing	Owner Occupied
15-35	34.2%	27.3%	13.3%	59.4%
36-50	48.3%	3.8%	18.0%	78.2%
51-65	1.7%	1.0%	8.2%	90.8%
65+	0.8%	0.3%	2.0%	97.7%
15-65	27.6%	11.6%	13.0%	75.4%

4.6 Results

Figure 4-4: Quintiles of Median Equivalised Household Disposable Income

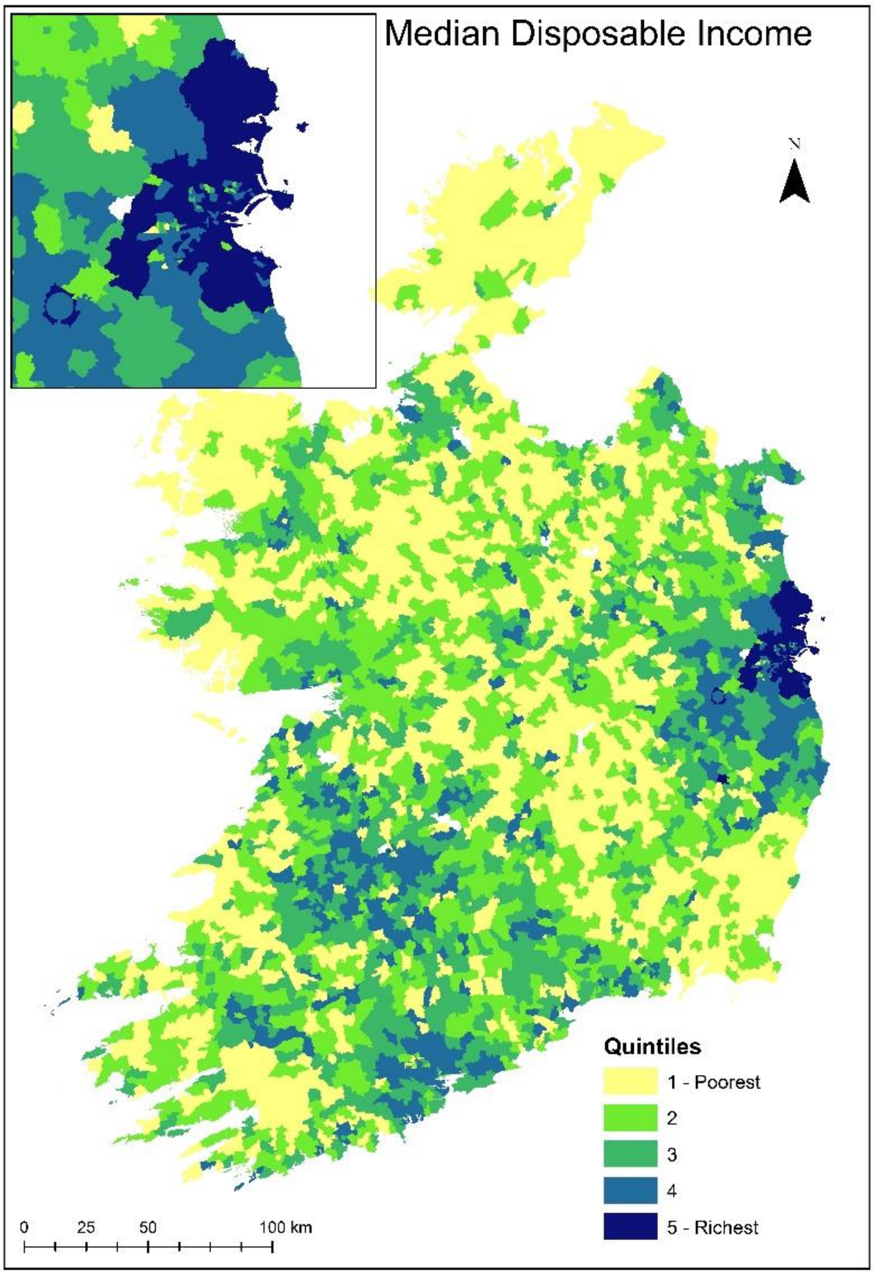
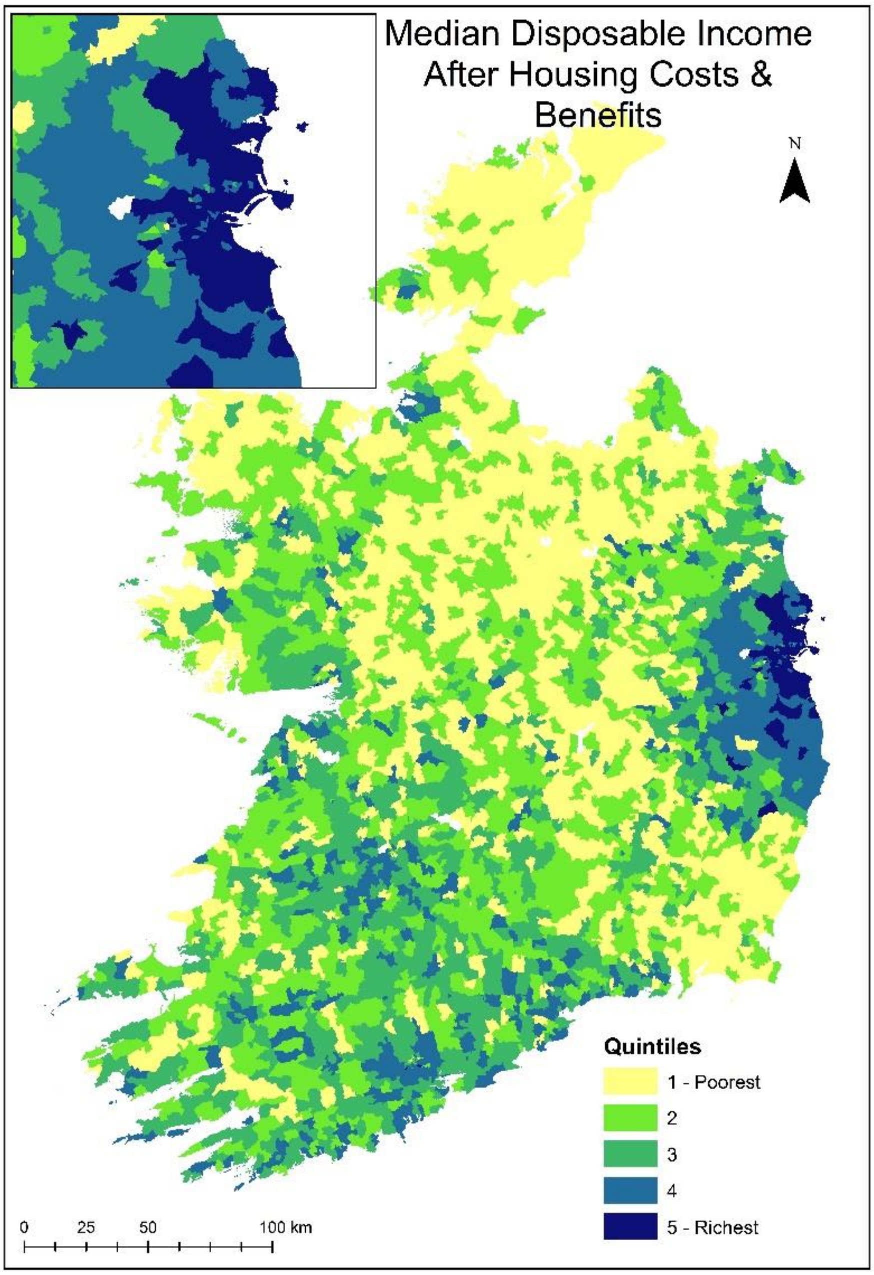


Figure 4-5: Quintiles of Median Equivalised Household Disposable Income including housing costs and benefits



Figures 4-4 and 4-5 show the spatial distribution of income before and after housing costs and benefits are considered. From Figure 4-4 we can a concentration of wealth in Dublin City and around the cities of Limerick and Cork. After we take into account housing costs and benefits (Figure 4-5), this concentration of wealth in Dublin has spread out into the GDA, while it has decreased around Limerick and Cork cities. The increase in wealth in the GDA is because of owner occupiers benefiting from higher rental and property values which leaves them with high net imputed rent values and high reverse mortgage annuities. Table 4-5 shows that although there is a lower amount of owner occupiers in Dublin City and County compared to rural areas, this is able to offset the costs inflicted upon those renting. The high net imputed rent and annuity values are masking an impact on a particular group.

Table 4-5: Housing Tenure by Urban-Rural Classification

Location	Population Share	Social Housing	Private Renting	Owner Outright	Has Mortgage	Owner Occupier
Rural	17%	15%	8%	59%	18%	77%
Village (200 – 1499)	15%	14%	9%	57%	19%	77%
Town (1500 – 2999)	6%	11%	8%	59%	21%	80%
Town (3000 – 4999)	3%	11%	8%	60%	21%	81%
Town (5000 – 9999)	7%	12%	10%	57%	20%	78%
Town 10000 +)	16%	13%	11%	56%	21%	77%
Waterford	1%	13%	11%	56%	20%	76%
Galway	2%	10%	12%	51%	26%	78%
Limerick	1%	17%	10%	54%	18%	73%
Cork	4%	12%	11%	57%	21%	77%
Dublin County	11%	13%	13%	52%	22%	74%
Dublin City	16%	12%	10%	56%	22%	78%

An examination of the movers shows us there are lifecycle effects taking place. Those who move down quintiles tend to have high levels of disposable income, low levels of imputed rent and annuity. They are younger areas and more likely to be educated and living in a less densely populated area. Those who move up tend to be older and have the characteristics of lower education, less likely to be employed and higher housing benefits. This would appear to be a lifecycle impact as there is a large movement up the income distribution by the elderly. This corresponds with what was previously found in the literature. The elderly benefit from having no mortgage rent, a net imputed rent and annuity income. This overcomes their lack of disposable income by pushing those in the lower age brackets down a quintile.

Table 4-6: Summary Statistics and Characteristics of Electoral Divisions Before and After the inclusion of housing costs and benefits and of the movers

	Before		After		Movers (quintiles)	
	Q1	Q5	Q1	Q5	Down 2 +	Up 2 +
Disposable income	€16,849	€28,252	€17,385	€27,200	€20,630	€17,920
Imputed Rent	€3,386	€7,652	€3,119	€7,664	€3,174	€4,520
Annuity	€4,845	€12,083	€4,186	€12,329	€3,831	€7,115
Costs	€1,357	€3,270	€1,376	€3,056	€1,642	€1,531
Youth Dependency	33.8%	24.3%	36.2%	24.1%	38.8%	28.9%
Old Age Dependency	23.0%	20.3%	20.6%	23.0%	15.3%	25.6%
University Educated	29.7%	45.1%	31.0%	42.4%	37.0%	30.3%
Employment Share	56.4%	64.2%	57.7%	62.6%	63.5%	57.2%
Unemployment share	14.2%	8.7%	13.8%	9.3%	11.6%	12.2%
Pop Density	292	4051	137	4029	405	907
Age	42.1	42.9	40.4	44.0	37.7	45.2
Work Age Share	64.0%	69.9%	64.0%	68.7%	65.2%	65.1%

An analysis of where these movers are located shows us that a majority are in Dublin County and rural areas. The high cost of renting and property prices in Dublin is having a negative impact. Even though workers in the GDA command a higher wage, when we take into consideration housing, this wage premium is being cancelled out.

Table 4-7: Quintile movers by Urban-Rural Classification

Location	Up % move	Down % move
Rural	24%	18%
Village (200 – 1499)	13%	16%
Town (1500 – 2999)	9%	10%
Town (3000 – 4999)	4%	3%
Town (5000 – 9999)	5%	3%
Town (10000 +)	14%	17%
Waterford	1%	8%
Galway	3%	0%
Limerick	1%	7%
Cork	19%	2%
Dublin County	0%	16%
Dublin City	6%	0%

Table 4-8 shows that much of the variation in incomes is occurring within rather than between regions. We can see that housing costs increases inequality from 0.309 to 0.368. However after taking into account the benefits overall inequality decreases to 0.272. For those who pay housing costs they will receive little of the benefits. These benefits which are large appear to cancel out the costs when we examine an overall area. It is important therefore to examine at a household level the impact of housing.

Table 4-8: Theil I2 Index of Disposable Income + or – the various housing costs and benefits

Variable	I2	Between	Within	Between %	Within %
Disposable Income	0.309	0.018	0.291	6%	94%
- Costs	0.368	0.016	0.353	4%	96%
+ Imputed Rent	0.257	0.022	0.235	9%	91%
+/- Net Imputed Rent	0.296	0.019	0.277	7%	94%
+Annuity	0.252	0.027	0.225	11%	89%
+/- Net Housing	0.272	0.029	0.243	11%	89%

One method is to look at the progressivity of the various housing measures. Table 4-9 report the Gini and Reynolds-Smolensky Indices. The Reynolds-Smolensky index measures the progressivity or regressivity of the various measures. From our results only the costs measure has a regressive impact on the distribution. An examination of the Gini coefficient shows that imputed rent is marginally greater than the regressive nature of housing costs.

Table 4-9: Gini Index and Reynolds-Smolensky Index of housing measures showing level of progressivity

	Disposable Income	Imputed Rent	Costs	Net Imputed Rent	Reverse Mortgage	Net Income
Gini of measure	0.284	0.252	0.307	0.270	0.228	0.220
Reynolds-Smolensky	-	0.063	-0.046	0.028	0.112	0.128

The Lorenz curves in Figure 4-6 and 4-7 illustrate this further. We can see that at the lower end of the income distribution income net of housing costs and benefits is increasing inequality over equivalised income but as we move along the income distribution the curves cross and it starts to reduce inequality at the upper end.

Figure 4-6: Population Lorenz Curves of Equivalised Income Before and After Housing Costs and Benefits

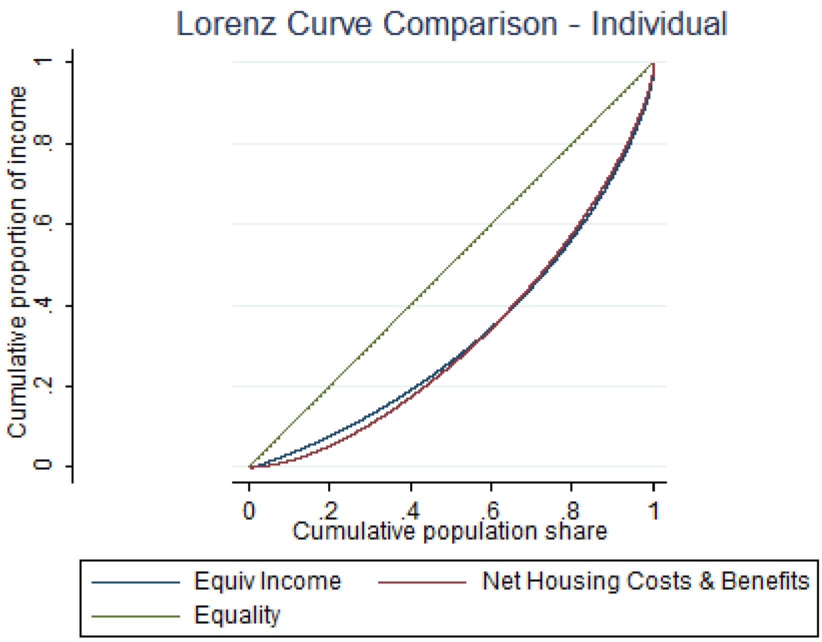


Figure 4-7: Electoral Division Lorenz Curves of Equivalised Income Before and After Housing Costs and Benefits

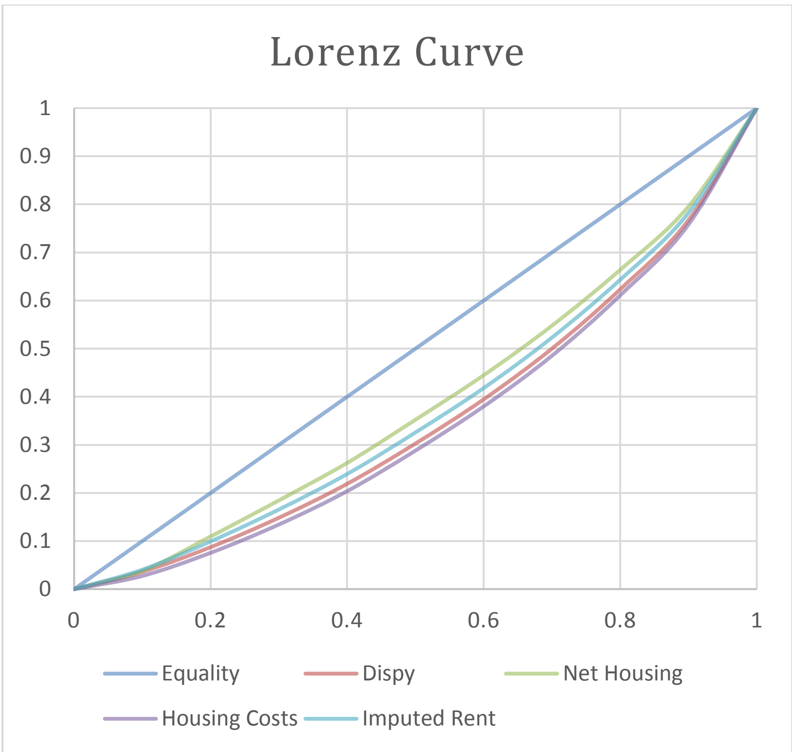


Table 4-10: Impact of Measure on Income Share

	Disposable Income		Housing Costs		Imputed Rent		Net Imputed Rent	
	% of median	Share %	% of median	Share %	% of median	Share %	% of median	Share %
1	51.64	3.22	43.50	1.83	49.78	3.18	40.65	1.86
2	62.35	4.41	60.04	4.06	64.90	4.66	61.25	4.22
3	73.53	5.22	71.66	5.05	76.89	5.72	75.51	5.60
4	85.79	6.12	85.37	6.01	87.78	6.64	87.76	6.66
5	100.00	7.24	100.00	7.11	100.00	7.55	100.00	7.64
6	117.75	8.23	117.68	8.33	114.95	8.63	114.94	8.75
7	141.64	9.93	143.37	9.98	135.41	10.04	135.80	10.18
8	174.97	12.08	178.35	12.31	164.27	11.99	165.14	12.21
9	229.45	15.30	234.72	15.67	212.36	15.00	214.56	15.30
10	0.00	28.26	0.00	29.65	0.00	26.60	0.00	27.59

Table 4-11: Impact of Reverse Mortgage and Housing on Income Share

	Reverse Mortgage		Net Housing	
	% of median	Share %	% of median	Share %
1	44.96	2.93	32.81	1.56
2	59.80	4.33	53.96	3.71
3	73.55	5.49	71.14	5.33
4	86.21	6.58	85.55	6.66
5	100.00	7.66	100.00	7.87
6	115.78	8.86	116.06	9.16
7	135.63	10.32	136.13	10.67
8	162.82	12.22	163.02	12.64
9	210.79	15.12	209.56	15.57
10	0.00	26.50	0.00	26.83

The share of income for those in the bottom decile has decreased from 3.22% to 1.56%. The income share for those in the top decile has also decreased, while it has increased for those in the middle who are now benefiting from the increase in utility. The poor quintiles are disadvantaged from paying housing costs and not receiving any of the in-kind benefits. This is widening the distribution but only for those under the age of 65 (Table 4-6). Elderly individuals who were in the bottom quintiles who were cash poor but asset rich have seen their income increase after housing costs and benefits are considered.

Table 4-12: Income Share After each Housing Benefit or Cost

	Disposable Income	Housing Costs	Imputed Rent	Net Imputed Rent	Reverse Mortgage	Net Housing
	Share %	Share %	Share %	Share %	Share %	Share %
1	3.22	1.83	3.18	1.86	2.93	1.56
2	4.41	4.06	4.66	4.22	4.33	3.71
3	5.22	5.05	5.72	5.60	5.49	5.33
4	6.12	6.01	6.64	6.66	6.58	6.66
5	7.24	7.11	7.55	7.64	7.66	7.87
6	8.23	8.33	8.63	8.75	8.86	9.16
7	9.93	9.98	10.04	10.18	10.32	10.67
8	12.08	12.31	11.99	12.21	12.22	12.64
9	15.30	15.67	15.00	15.30	15.12	15.57
10	28.26	29.65	26.60	27.59	26.50	26.83

4.7 Conclusions

Previous studies of imputed rent have been restricted to an aspatial scale due to a lack of income data with a spatial component (Balcázar et al., 2014). This study has been able to benefit from the use of spatial microsimulation to examine imputed rent at a small area level. This spatial information has allowed us to use spatial methods to estimate rent and property prices at a detailed spatial scale and link these values back to individuals.

This paper has shown the value of including in-kind benefits into the calculation of disposable income and individual welfare. Owner occupied housing greatly increase an individual's potential to consume. When we take into account housing costs in the form of rents and mortgage payments and housing benefits in the form of imputed rent and reverse mortgage annuities, the spatial distribution of welfare changes. On average the wealth of the GDA increases however when we examine the movers more closely the high rents and property values in the GDA are masking the high costs young workers are facing. The net gain to owner occupiers exceeds the net loss to renters. The inequality measures however have shown that overall housing costs and benefits are having a regressive impact on the income distribution with those at the lower end of the income distribution disproportionately affected.

Inequality however is not increasing for all age groups and there are clear benefits for older age categories. Reverse mortgage annuity has great potential for those who are 65+. Perhaps people should view reverse mortgage as a type of pension which they have paid into over the term of the mortgage. They can then draw down this pension upon retirement. Similar to previous studies we find the stream of consumption value provided by housing compensates the elderly who are cash poor but asset rich.

In terms of policy implications, it would be worthwhile to examine a tax on imputed rent which would go towards reducing the inequality between those who own a house and those who are renting. The current LPT is levied on all properties despite the fact private renters do not receive the same level of benefits from housing as owner occupiers. The life-cycle impacts suggest this tax should be dependent on age so there is an incentive for those in the older age categories to take out a reverse mortgage.

The high rental values particularly in the GDA may hinder an individual's ability to save to take out a mortgage. Solutions are required to increase an individual's potential to save. The latest generation have much lower levels of owner occupation compared to previous. We have seen the benefit of owner occupation especially to the elderly. If this trend continues the elderly will be particularly vulnerable as they will be cash poor and asset poor.

Chapter 5. The Spatial Impact of Commuting on Income: a Spatial Microsimulation Approach[16]

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5.1 Abstract

The Irish economic boom resulted in a substantial increase in car-ownership and commuting. These trends were particularly noticeable in the Greater Dublin Area (GDA), with an unprecedented increase in employment levels and private car registrations. While employment dropped by an overall 6 % during the recent economic recession, the already increasing process of suburbanisation around Irish main cities continued. The commuting belt around Dublin extended beyond the GDA with a substantial number of individuals commuting long distances. The aim of this paper is to examine the impact of both monetary and non-monetary commuting costs on the distribution of employment income in Ireland. The Census of Population is the only nationwide source of information on commuting patterns in Ireland. However, this data set does not include information on individual income. In contrast, SMILE (Simulation Model for the Irish Local Economy) contains employment income data for each individual in Ireland. Using data from the Census of Population of Ireland, discrete choice models of commuting mode choice are estimated for three subsamples of the Irish population based on residential and employment location and the subjective value of travel time (SVTT) is calculated. The SVTT is then combined with the SMILE data to produce a geo-referenced, attribute rich dataset containing commuting, income, demographic and socio-economic data. Results show that the monetary and non-monetary costs of commuting are highest among those living and working in the GDA.

5.2 Introduction

Increasing commuting distances has been negatively associated with the growing patterns of suburbanisation experienced in developed economies (Lyons and Chatterjee, 2008, Sultana and Weber, 2007). Commuting is a mechanism to balance the geographical mismatch between the supply and the demand for labour. According to the

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traditional urban economic theory, residential location is the result of the trade-off between commuting costs and housing costs (Alonso, 1964, Mills, 1972, Muth, 1969). Households decide to locate their residence further from work and have greater commuting costs in exchange for lower housing costs. In contrast to this model, search theory assumes that labour and housing markets are not perfectly competitive and that workers cannot fully minimise their commuting costs (Rouwendal, 2004, Van Ommeren and Rietveld, 2007, van Ommeren et al., 1999a). According to search theory, increasing commuting distances are the outcome of a job search process where longer commutes have been traded for higher wage rates (Westin and Sandow, 2010). Contemporary workforce specialisation gives rise to labour markets offering few potential jobs within 'reasonable' distance, and therefore give rise to so-called 'thin labour markets' (Manning, 2003, Sandow and Westin, 2010). Therefore, the impact of the labour market on commuting behaviour relates to workers' skills and occupations, with a direct relationship between high education levels and increased mobility and commuting distances (Eliasson et al., 2003, Gruber, 2010, Hazans, 2004, Prashker et al., 2008, Sandow, 2008, Van Ham, 2001).

This research is concerned with the impact of commuting behaviour on the spatial distribution of employment income in Ireland. Evidence suggests that increased employment in professional and managerial posts in the Greater Dublin Area (GDA) and other Irish cities has led to higher salaries in these areas (Morrissey and O'Donoghue, 2011). At the same time, levels of commuting have increased across the country, particularly in the GDA (Commins and Nolan, 2011, Vega and Reynolds-Feighan, 2009). Total commuting costs, being the sum of monetary and time costs, can be quite substantial. For a worker with an eight-hour working day and a one-way commute of half an hour, the total commuting costs are estimated to be about 10 percent of the daily wage (Rouwendal and van Ommeren, 2007). About 70% of these costs are due to time costs and about 30% due to monetary costs (Rouwendal and van Ommeren, 2007, Small and Verhoef, 1992).

While travel distance and the subsequent cost burden on individuals have been of interest to transport researchers for some time (Jara-Díaz, 2000), much of this research has focused on quantifying the cost of commuting across different locations and socio-economic groups (Hazans, 2004). With the exception of Hazans (2004) work on commuting patterns in Estonia, Latvia and Lithuania, where commuting was shown to substantially reduce wage differentials between capital cities and rural areas, as well as between capital cities and other cities, little research has sought to account for the cost of commuting on employment income. This lack of research is not due to lack of policy interest in this area, but rather to address such a question a variety of microdata containing both commuting and income data is required (Lovelace et al., 2014).

The aim of this paper is to examine the impact of both monetary and non-monetary commuting costs on the distribution of employment income in Ireland. The Census of Population of Ireland is the only nationwide source of information on commuting patterns in the country. However, this data set does not include information on individual income. In contrast, SMILE (Simulation Model for the Irish Local Economy) contains employment income data for each individual in Ireland. The paper combines both methodologies to present a unique dataset for Ireland that enables us to obtain the spatial distribution of the impact of commuting on employment income at the electoral division (ED) level.

Linking spatial microsimulation models to exogenous models provides a powerful tool for examining a wider range of policy questions (Morrissey et al., 2008, Smith et al., 2006, Tomintz et al., 2013, Van Leeuwen, 2010). Spatial microsimulation is a means of synthetically creating large-scale micro-datasets at different geographical scales. The development and application of spatial microsimulation models offers considerable scope and potential to analyse the individual composition of an area so that specific policies may be directed to areas with the greatest need for that policy (Birkin and Clarke, 2012). To date a number of techniques have been developed to produce spatial microsimulation models, including Iterative Proportional Fitting (IPF), deterministic reweighting (Ballas et al., 2005a), combinational optimisation (Voas and Williamson, 2001) and GREGWT (Lymer et al., 2008). Each of these methods results in the synthesis of spatial microdata by combining small area census data with survey data. In other words, the models simulate virtual populations to match real aggregate data (Birkin and Clarke, 2012, Tanton, 2014)

Using data from the 2011 Census of Population of Ireland, discrete choice models of commuting mode choice are estimated for three sub-samples of the Irish population based on residential and employment location. The subjective value of travel time (SVTT) is then calculated for each of these areas. This value of travel time is then combined with the SMILE data to produce a unique geo-referenced, attribute rich dataset containing commuting, income, demographic and socio-economic data. Such a dataset currently does not exist for Ireland. However, linking data created by a spatial microsimulation model within a travel to work framework provides the necessary data to examine the relative impact of commuting on the spatial distribution of employment income at the small area level in Ireland. Results from this research also extend previous research on commuting in Ireland (Commins and Nolan, 2010, Commins and Nolan, 2011).

The paper is structured as follows: the next section provides a detail account of the spatial microsimulation methodology and data used in the paper. Section 3 provides a theoretical introduction to the value of travel time and the modelling framework, followed by data and estimation results. Section 4 shows the results obtained from linking the travel demand model and the SVTT with the spatial microsimulation model. Section 5 includes the discussion of the results.

5.3 Spatial Microsimulation: Data and Methods

In order to model the impact of commuting travel times on employment income, spatially referenced micro-data is required. Small Area Population Statistics (SAPS) data contains census information disaggregated to the electoral division level. Electoral Divisions (EDs) are the smallest legally defined administrative areas in Ireland. There are 3,440 EDs with a mean population of 1,346 (S.D=2,197), ranging from 73 to 36,057 individuals. Based on the SAPS dataset, the Place of Work School Census of Anonymised Records (POWSCAR) dataset for 2011 is geographically referenced (ED level) commuting dataset for Ireland. For the first time, POWSCAR 2011 contains detailed commuting data for the entire population both adults and children. All workers resident in Ireland on Census night were coded to their place of work and all Irish resident students from the age of 5 and upwards were coded to their place of school/college. The commuting data contained in POWSCAR includes residential ED location; work ED Location, distance to work, travel time to work and mode choice. However, similar to SAPS, POWSCAR does not contain income information. In contrast, household survey data such as the Survey of Income and Living Conditions (SILC) contains income and employment information at the individual and household level.

The SILC is a nationally representative 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. 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, which contains two regions, the Border, Midlands and West region and the South East region). As such, any analysis using the SILC survey is constrained to the national level. Furthermore, the SILC dataset does not contain commuting data. Using a matching algorithm to link the data in the SILC with the small area level SAPS and POWSCAR data, a much richer dataset would be obtained that would allow an examination of the variations in the value of commuting travel times relative to disposable income across the Irish regions and spatial microsimulation techniques can be used to accomplish this.

SMILE was developed by the Rural Economy Development Programme (REDP), Teagasc and the School of Geography, University of Leeds (Ballas et al., 2006b, Morrissey et al., 2008). The first version of SMILE, referred to as SMILE2002 for the purpose of this paper, was based on 2002 Census of Population data and the Living in Ireland Survey (2001) and used a combinational optimisation algorithm, simulated annealing (Morrissey et al., 2008). However, although simulated annealing allows 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 the simulation (Farrell et al., 2012a, Hynes et al., 2009b). As a result, to create SMILE 2006 and SMILE 2011 and match the Small Area Population Statistics (SAPS, 2011), SILC (2010) and POWSCAR (2011) datasets, a more computationally efficient method known as quota sampling (QS) was developed by Farrell et al. (2012a)).

QS requires both the spatially referenced aggregate data and micro level datasets outlined above. 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. For both SMILE 2006 and 2011, these quotas are provided by the SAPS dataset. Five matching constraints were used in developing SMILE 2011; these include the number of individuals in each ED, the number of households in each ED, the number of individuals in each household, a tabulated age, sex variable and education level. In 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., 2012a).

In practice, the implementation of QS raises a number of issues (Farrell et al., 2012a, Morrissey et al., 2014). These issues include a bias towards sampling smaller households, an inability to adequately simulate certain demographic groups due to disparities between survey and census data distributions and difficulties in allocating the final few households due to the increasingly restrictive nature of quota counts as the simulation progresses. To overcome these issues an ordered constraint procedure where groups that are difficult to allocate, particularly large households and households containing children, are selected first (Farrell et al., 2012a). Following this step, the sampling procedure admits under-represented groups. Finally, to overcome prohibitively restrictive quota counts, a process similar to the swapping of households in simulated annealing is required (see Morrissey et al. (2008)). This is achieved by removing each constraint one by one until the quota is met. Constraints are removed in reverse order of the degree to which they influence household income (Farrell et al., 2012a). This is determined by pre-synthesis regression analysis (Edwards and Tanton, 2012). This design minimises subjectivity, whereby the broadening of constraints is only introduced when absolutely necessary and in a manner, which ensures that, variables that explain the greatest level of variability are retained to the greatest extent. Generally all quotas are filled and this stage is skipped. As noted by Farrell et al. (2012a) ordering the constraints in such a manner may cause validation issues to arise, in that the distribution for larger households or under-represented groups may be less robust. However, any modelling method that aims to simplify real-world complexity will have issues. To decrease these issues, validation of the QS output is an integral component of the model's construction.

Calibration

The computation cost of QS and other methods of generating small area data limit the number of constraints one can use (Farrell et al., 2012a, Morrissey and O'Donoghue, 2011). However the spatial heterogeneity of the simulated data depends upon achieving the correct multivariate relationship with non-constraining variables, as well as the constraining variables. 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, Morrissey et al., 2013). The purpose of the calibration procedure is to align the small area level data within SMILE with exogenous data on labour force participation and income. The procedure 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 and application of the calibration method in terms of labour force and income distributions and socio-economic characteristics and health service utilisation is provided by Morrissey and O'Donoghue (2011) and Morrissey et al. (2013), respectively.

Using a probabilistic alignment technique the spatial distribution of unconstrained labour market characteristics are calibrated against their original 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 data (CSO, 2011). 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 (Morrissey et al., 2014).

Finally, the newly calibrated data must be validated to ensure that the alignment process was successful and that the newly calibrated micro level income data represents the exogenous income totals. The newly calibrated data was validated using an external, out-of-sample validation technique (Caldwell, 1996). Out-of-sample validation involves comparing the synthetically created microdata with new, external data. From a spatial perspective, the income data was validated against the county income estimates at the county level, while the weighted SILC was used to validate income estimates at the regional level. Table 5-1 presents the result of the income validation at the county level. Examining the real CSO income estimates and the simulated estimates on can see that although definitional issues arise when linking micro and macro level data, the simulated income data is very close to CSO data, with an average percentage difference of less than 1%. Sligo showed the lowest percentage difference between the simulated and CSO data, with a 0.01% difference. The simulated data for both Offaly, Monaghan and Meath had the highest difference, 4.24%, 3.91% and 3.27% respectively. It is however important to note that comparing the rank distributions between the CSO and simulated data that Meath maintains its distribution rank (6 CSO, 6 simulated data). The difference between the CSO and simulated data for Monaghan is however larger (23 CSO, 18 simulated). Thus, the SMILE alignment procedure still over estimates the average income in County Monaghan. Overall, with regard to the difference in rank between the CSO and simulated data, it was found that the cross county distribution of income was mostly maintained with Dublin having the highest income per person and Donegal the lowest.

Table 5-1: Validation of the Simulated Income Data at the County Level

County	CSO €	SMILE €	Real Difference €	% Difference	CSO Rank	SMILE Rank
Dublin	28,834	29,297	464	1.61%	1	1
Limerick	26,743	26,094	-649	-2.42%	2	2
Kildare	25,346	25,100	-247	-0.97%	3	3
Wicklow	24,560	24,595	34	0.14%	5	4
Cork	24,621	23,973	-648	-2.63%	4	5
Meath	24,218	23,425	-793	-3.27%	6	6
Waterford	22,922	23,410	488	2.13%	7	7
Louth	22,698	23,371	673	2.96%	9	8
Clare	22,266	22,840	573	2.57%	13	9
Tipperary North	22,490	22,838	349	1.55%	10	10
Tipperary South	22,483	22,534	51	0.23%	11	11
Westmeath	21,868	22,331	463	2.12%	15	12
Galway	22,755	22,218	-537	-2.36%	8	13
Carlow	22,345	22,081	-265	-1.18%	12	14
Sligo	22,002	22,004	2	0.01%	14	15
Kilkenny	21,711	21,512	-199	-0.92%	17	16
Mayo	21,127	21,350	223	1.06%	20	17
Monaghan	20,482	21,282	800	3.91%	23	18
Kerry	20,929	21,243	314	1.50%	21	19
Leitrim	21,833	21,107	-725	-3.32%	16	20
Longford	20,471	21,039	568	2.78%	24	21
Wexford	21,255	20,969	-286	-1.35%	19	22
Offaly	20,071	20,922	851	4.24%	26	23
Laois	21,545	20,878	-667	-3.09%	18	24
Cavan	20,621	20,597	-24	-0.12%	22	25
Roscommon	20,413	20,563	150	0.74%	25	26
Donegal	19,097	19,224	127	0.67%	27	27

5.4 Travel to Work Model

Since the economic theory of the valuation of time was first introduced in the 1960s, the subject of time allocation has been explored from different perspectives. Becker (1965) was the first to introduce the cost of time in the traditional theory of choice, with the idea of a value attached to the time assigned to particular activities. Under Becker's

(1965) theory, individual satisfaction came from *final goods*, with market goods and time for preparation and consumption as necessary inputs. Soon after Becker's (1965) paper, this theory was re-formulated by Johnson (1966) and later by Oort (1969) to incorporate work time and travel time into the basic utility function. Their research showed that including work time within the utility function led to a value of time equal to the wage rate plus the subjective value of work, which is the ratio between the marginal utility of work and the marginal utility of income (Jara-Díaz, 2000).

The daily trip to work is ubiquitous, yet its characteristics vary from person to person and place to place (Lovelace et al., 2014). An individual must choose between a set of discrete alternatives (transport modes), given the choices that are available to them. Following research by Train and McFadden (1978), the analysis of travel behaviour has been increasingly based on disaggregated data within discrete choice models. Discrete choice models may be used to estimate the probability of an individual decision-maker choosing particular alternative from a set of alternatives, as a function of the attributes of the choice and the demographic and socio-economic characteristics of the individual (Commins and Nolan, 2011). Similar to the original research by Becker (1965), these models are grounded in consumer utility theory whereby the individual chooses among alternatives with the aim of maximising personal utility depending on *G*, the volume of goods and services they can buy, *L*, the amount of 'leisure' time they have, and *T* the amount of time they have to spend travelling. Travel can occur by different modes *i*, involving different costs and travel times. Since total money and time budgets are fixed, travel costs and times impact on the amount of other goods and the amount of leisure time available. The problem can be set out as a utility maximisation problem follows:

$$\text{Max } U(G_i, L_i, T_i)$$

subject to

$$G_i \leq M - c_i(\lambda) \qquad (1)$$

$$L_i \leq T - T_i(\mu)$$

$$T_i^* \leq T_i(\psi_i)$$

where *M* is the total money budget available, c_i is the cost of travel associated with mode *i*, T_i* is the minimum travel time by mode *i* and *T* is the total time available. The three Lagrangean multipliers associated with each of the restrictions to the problem above, λ, μ, ψ_1, …, $\psi_M \geq 0$, can be interpreted as follows: λ is the marginal utility of income or money (the shadow price of relaxing the budget constraint), μ is the marginal utility of time in terms of relaxing the total time constraint, and ψ_i is the marginal utility due to relaxing the minimum travel time of mode I (Bates, 1987). After carrying out a first order approximation of the direct utility, Bates (1987) obtains the following formulation:

$$V_i = \alpha_i + \beta_c c_i + \beta_{T_i} T_i \quad (2)$$

where the cost parameter coincides with the negative of the marginal utility of income ($\beta_c = -\lambda$) and the travel time parameter for mode i is equal to the negative of the marginal utility of relaxing the minimum travel time of model I ($\beta_{T_i} = -\psi_i$) . This formulation justifies the introduction of travel time and travel cost as explanatory variables of modal choice. Also, given that these parameters can be interpreted as marginal utilities, the marginal rate of substitution between time and money corresponds to the β_{T_i}/β_c ratio. This can be interpreted as the marginal propensity to pay to save travel time by a given mode, which is what is generally known as the subjective value of travel time (SVTT), (Mackie and Nellthorp, 2001).

5.5 Data

The data used in this paper for the travel to work model comes from the Place of Work Census of Anonymised Records (POWSCAR) from the 2011 Census of Population of Ireland. Due to the substantial difference in population density and public transport provision, the model is estimated for 3 sub-regions: (i) Greater Dublin Area – Dublin County Borough, Fingal, South Dublin, Dun-Laoghaire-Rathdown, Kildare, Meath, Wicklow and Louth, (ii) Other Provincial Cities – Cork, Limerick, Galway and Waterford and (iii) Other Towns and Rural Areas. Table 5-2 shows the commuting patterns of the three sub-regions.

Table 5-2: Commuting patterns of sub-regions

	Greater Dublin Area	Other Provincial Cities	Other Towns and Rural Areas
Definition	Dublin County Borough, Fingal, South Dublin, Dun Laoghaire-Rathdown, Kildare, Meath, Wicklow and Louth	Cork, Limerick, Galway and Waterford	Elsewhere
Modal share			
Car (%)	78	96	98
Public Transport (%)	22	4	2
Average commuting distance	22.4	17.2	19.8
Resident working population	518,580	261,515	357,329

Source: POWSCAR, 2011

The sample excludes those working from home and those with a mobile place of employment. To ease the computational burden, a 10 per cent random sample is used to estimate the models. Each observation contains socio-economic information such as age, gender, household type, housing tenure, marital status, education level, socio-economic group and industrial group, as well as the land use characteristics of the electoral divisions for the origin-destination journey to work, travel time, distance and main mode of transport. All variables are self-reported.

In this application, an individual chooses between two modes of travel to work: (1) Motorcycle, Car Driver or Car Passenger and (2) Bus or Train. Mode availability is taken into account in the estimation process and the probabilities are computed accordingly. The attributes of the alternatives and the characteristics of the decision maker included are those typically used for modelling travel mode choice. While (self-reported) travel times for the chosen modes of travel to work are available in the data, the travel times for the non-chosen modes are not. The method employed by De Palma and Rochat (2000) is used to estimate the travel times for the non-chosen alternatives in the data set. A comprehensive analysis of the alternative formulations for generating a travel time variable for Ireland was carried out in Commins and Nolan (2010), where

De Palma and Rochat's (2000) approach was found to be the most robust method in this regard. Travel cost information is constructed as a basic measure of cost per kilometre using information on 2006 public transport fares and the overall cost of driving a car (including insurance, tax, depreciation and fuel costs) from the National Transport Authority of Ireland. In addition to the alternative-specific variables, a number of socio-economic variables are used for the analysis. These include the gender, age, education level, socio-economic group, the nature of residential occupancy and the residential and employment location. Variable definitions are presented in Table 5-3.

Table 5-3: Variable definitions, POWSCAR 2011

	Definition
Third level Education	=1 if highest level of education completed is third level (reference category=less than third level)
Working in Dublin City	=1 if the job destination electoral division is Dublin City (reference category=job destination other than Dublin City)
Age 15-34	Reference category
Age 35-64	=1 if aged 35-64 (reference category = Age 15-34)
Age 65+	=1 if aged over 65 years (reference category = Age 15-34)
Number of cars in household	Total number of cars available in the household
Residential location in Co. Meath, Co. Kildare, Co. Louth or Co.Wicklow	=1 if the residential electoral division is in one of the commuting counties of Meath, Kildare, Louth or Wicklow
Female	=1 if female (reference category=male)
Rent	=1 if in rented accommodation (reference category = house owner)
Employers and managers, higher and lower professionals	Ref.
Non-manual	=1 if employee classified as non-manual worker (reference category = Employers, managers, higher and lower professionals)
Manual-skilled, semi-skilled and unskilled	=1 if employee classified as manual-skilled, semi-skilled or unskilled (reference category = Employers, managers, higher and lower professionals)
Travel time (hours)	Travel time spent in the journey to work
Travel cost (Euro)	Travel cost incurred in the journey to work

5.6 Estimation Results

The results of the discrete choice model for the three regions under analysis are shown in Table 5-4. Version 1.8 of Bierlaire Optimization Toolbox for General Extreme Value Model Estimation (BIOGEME) was used to estimate the model (Bierlaire, 2003, Bierlaire, 2009). BIOGEME is a freeware package designed for the development of research in the context of discrete choice models in general, and of Generalized Extreme Value models in particular (McFadden, 1978).

Overall, the results are consistent with those previously reported in previous studies by Commins and Nolan (2010; 2011) for the same study area. The probability of driving to work is significantly lower for those with third-level qualifications living in the GDA. This is consistent with previous results for the same region (see Commins and Nolan, 2011 for details). A possible explanation may have to do with the potential environmental awareness of those with higher levels of education who may prefer to use public transport alternatives. However, this is not the case in other provincial cities and towns and rural areas, where the opposite pattern is observed. This may respond to the well-documented lack of public transport options outside the capital city (Rau and Vega, 2012).

In terms of the land use dummy variable for the GDA model, those working in Dublin City are less likely to use their private car to commute to their workplace. In the case of the GDA, age is a significant predictor of the choice of mode of travel. Older individuals are more likely to use the car in comparison with those aged 15-34. As expected, high car ownership in the household is a strong predictor of the level of car use across the entire country. Those living in the so-called "commuter counties" of Meath, Kildare, Wicklow and Louth are significantly more likely to travel to work by car.

Being female is associated with an increase probability of travelling by public transport in all areas, but the estimates are non-significant outside the GDA. When compared with those who own their residential property, individuals in rented accommodation have an increased probability of travelling by public transport.

Table 5-4: Estimation results (reference choice is car)

	Greater Dublin Area	Other Provincial Cities(Cork, Limerick, Galway and Waterford)	Other Towns and Rural Areas
Individual-specific variables			
Third level Education	-0.14***	0.28***	0.59***
Working in Dublin City	-1.65***	-	-
Age 15-34	Ref.	Ref.	Ref.
Age 35-64	0.69***	0.46***	0.33***
Age 65+	0.75***	0.13	0.83
Number of cars in household	1.09***	1.31***	1.71***
Residential location in Co. Meath, Co. Kildare, Co. Louth or Co.Wicklow	1.02***	-	-
Female	-0.09***	-0.19	-0.93
Rent	-0.45***	-0.33***	-0.56***
Employers and managers, higher and lower professionals	Ref.	Ref.	Ref.
Non-manual	-0.30***	-0.65***	-0.80***
Manual-skilled, semi-skilled and unskilled	0.27***	-0.14	0.53***
Alternative-specific variables			
ASC car	0.58***	0.26	0.34***
ASC public transport	Ref.	Ref.	Ref.
Travel time (hours) - Car	-1.64***	-3.35***	-1.05***
Travel cost (Euro)	-0.16***	-0.15***	-0.17***
Number of observations	17,697	25,917	15,570

*** Significant at 5 per cent level.

With regard to the socio-economic group, individuals classified as manual-skilled, semi-skilled and unskilled are more likely to use a private car in the GDA and Other Towns and Rural Areas than the reference category. This contrasts with the estimates obtained for non-manual workers when compared with those in the top socio-economic group in each of the three regions, who are less likely to use their private car.

The alternative-specific estimates for travel time and travel cost are highly significant in all sub-regions. A generic specification is presented in the paper. According to the theoretical framework presented in Section 2, it is expected that the estimates for the travel time and travel cost variables present a negative sign. The subjective value of travel time (SVTT) in Euros per hour is shown in Table 5-5.

Table 5-5: Subjective values of travel time for commuting (Euro/Hour)

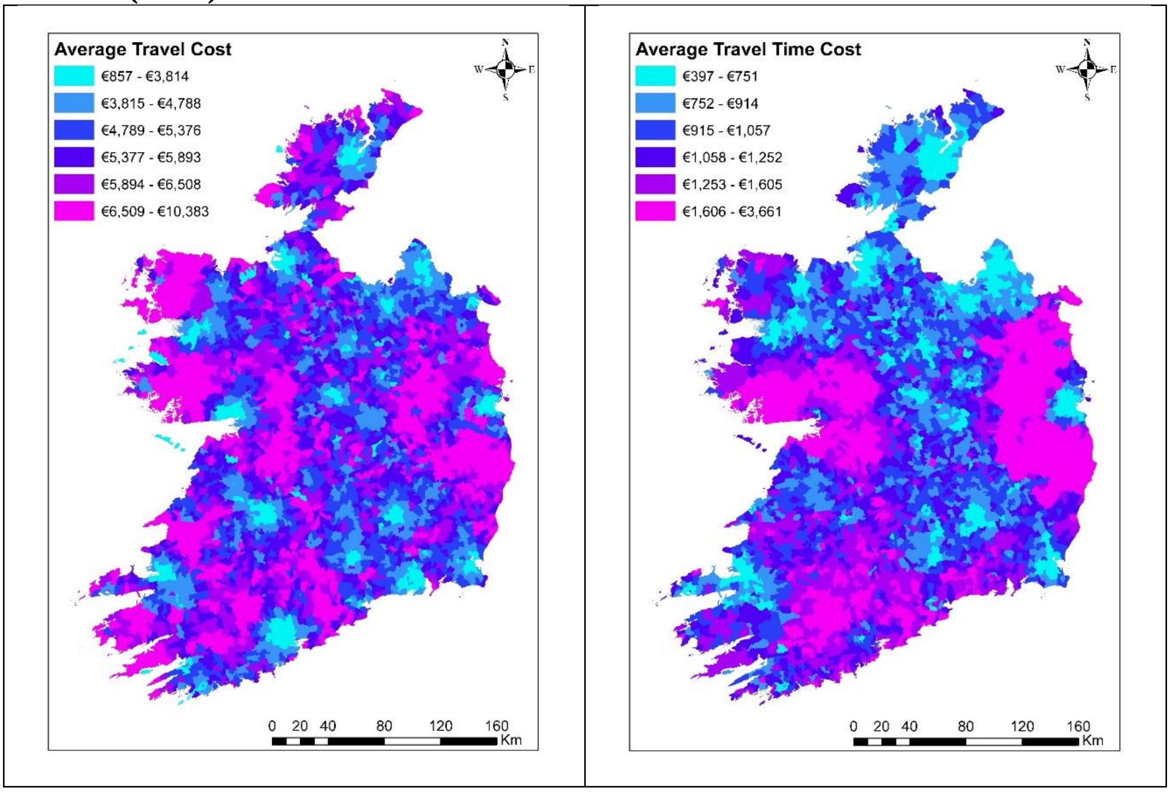
	Commuting VoT (Euro/h)
Greater Dublin Area	10.2
Dublin	8.96
Commuting Counties	14.1
Other Provincial Cities	21.2
Other Towns and Rural Areas	6.07

In the GDA, the SVTT for commuting is €10/hour. The largest SVTT is obtained for other provincial cities, while the SVTT for commuters in Other Towns and Rural Areas is substantially lower. A possible explanation for this result is that those areas included under other provincial cities are primarily comprised of urban and sub-urban districts, possibly subject to heavy traffic congestion due to limited public transport options and in some cases, longer commuting distance. Overall, the values obtained from the analysis are in line with those used by the Department of Transport Common Appraisal Framework (DTTAS, 2016).

5.7 Combining the Travel Demand Model with SMILE

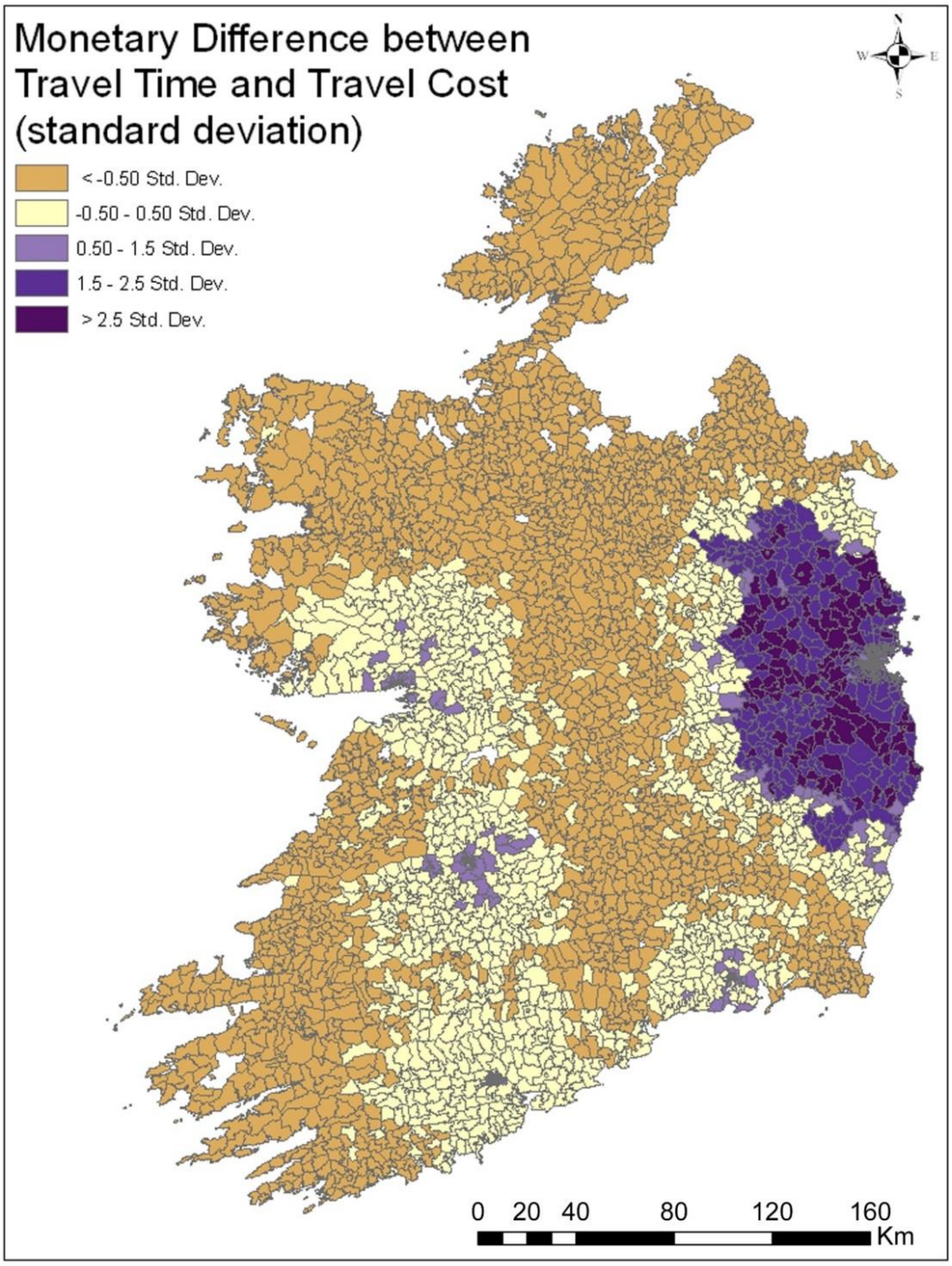
Once the travel demand model has been estimated using the POWSCAR dataset, the estimates are merged with the employment income data produced by SMILE to obtain the spatial distribution of the impact of commuting relative to employment income at the ED level. It is important to note that employment income refers to income derived from employee or self-employed based work in its gross form. Using small area level referenced microdata extends the previous research on commuting in Ireland outlined above (Commins and Nolan, 2010; 2011; Nolan, 2011). Figures 5-1a and 5-1b show the spatial distribution of the average monetary travel cost and travel time at the electoral division level for Ireland. While the average travel cost does not show clear spatial patterns, there are strong urban effects in the average travel time, which is notably higher around main urban areas and it is particularly evident in the case of the GDA. Figure 5-2 shows the standard deviation from the mean difference between average travel cost and travel time. Results show that electoral divisions with a significant difference between both travel indicators are found across Dublin's commuting districts and along the main transport corridors into the capital, which tend to be subject to high congestion levels.

Figure 5-1 a&b : Spatial distribution of average travel costs and travel times in Ireland (Euro)



Source: SMILE, 2011

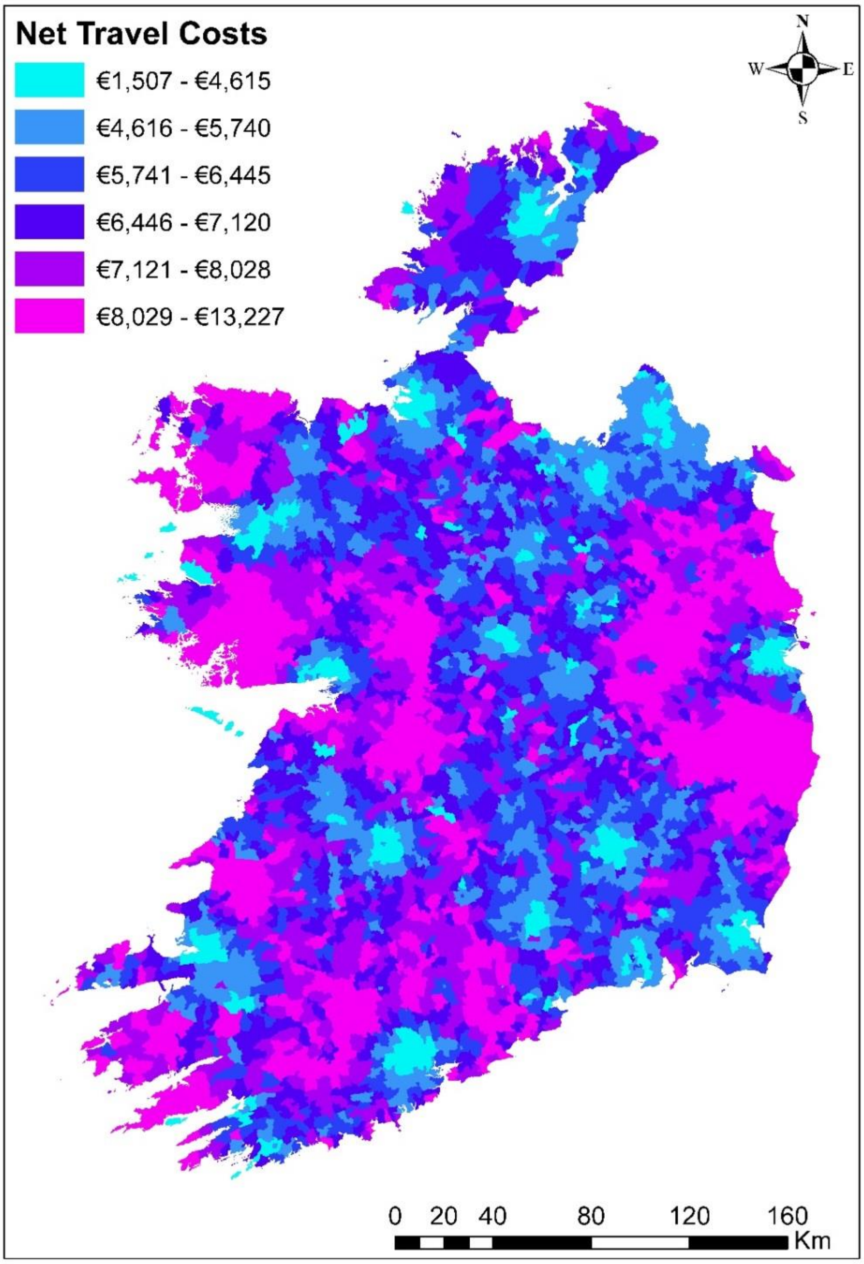
Figure 5-2: Spatial distribution of the monetary difference between travel cost and travel time in Ireland (standard deviation)



Source: SMILE, 2011

The data presented in this paper shows the consequences of the Irish economic boom, which resulted in a substantial increase in car-ownership and commuting (Brady and O'Mahony, 2011). These trends were particularly noticeable in the GDA, which saw an increase in employment by 48.9% and private car registrations by over 60% over the period 1996-2006 (Brady and O'Mahony, 2011). Research by Morgenroth (2002) found that during this period, the commuting belt around Dublin extended beyond the GDA and that a substantial number of individuals commuted long distances. While there was a decrease in levels of commuting in 2011 as a result of the economic downturn, the effects of the recent economic boom are still visible. Within this context, Figure 5-3 provides the net travel cost (NTC) at the small area level for Ireland. This measure takes into account for each ED the monetary cost per kilometre as well as the monetary cost per minute of commuting. The commuter counties within the GDA - Meath, Kildare, Wicklow and Louth - show the highest net travel cost in the country (€8,205 - €13,227). Figure 5-3 also shows the spatial distribution of net travel costs of other Irish cities, with particularly high levels found around the hinterlands of Galway and Cork. Meredith and Van Egeraat (2013) note that Galway (12%) and Cork (20%) have seen the highest increase in employment between 2001 and 2006, which may partially explain the high levels in net travel costs. Rural areas in the West, North West and South West have the lowest net travel costs. However, these regions are characterised by high farming rates, particularly in comparison to the East of the country.

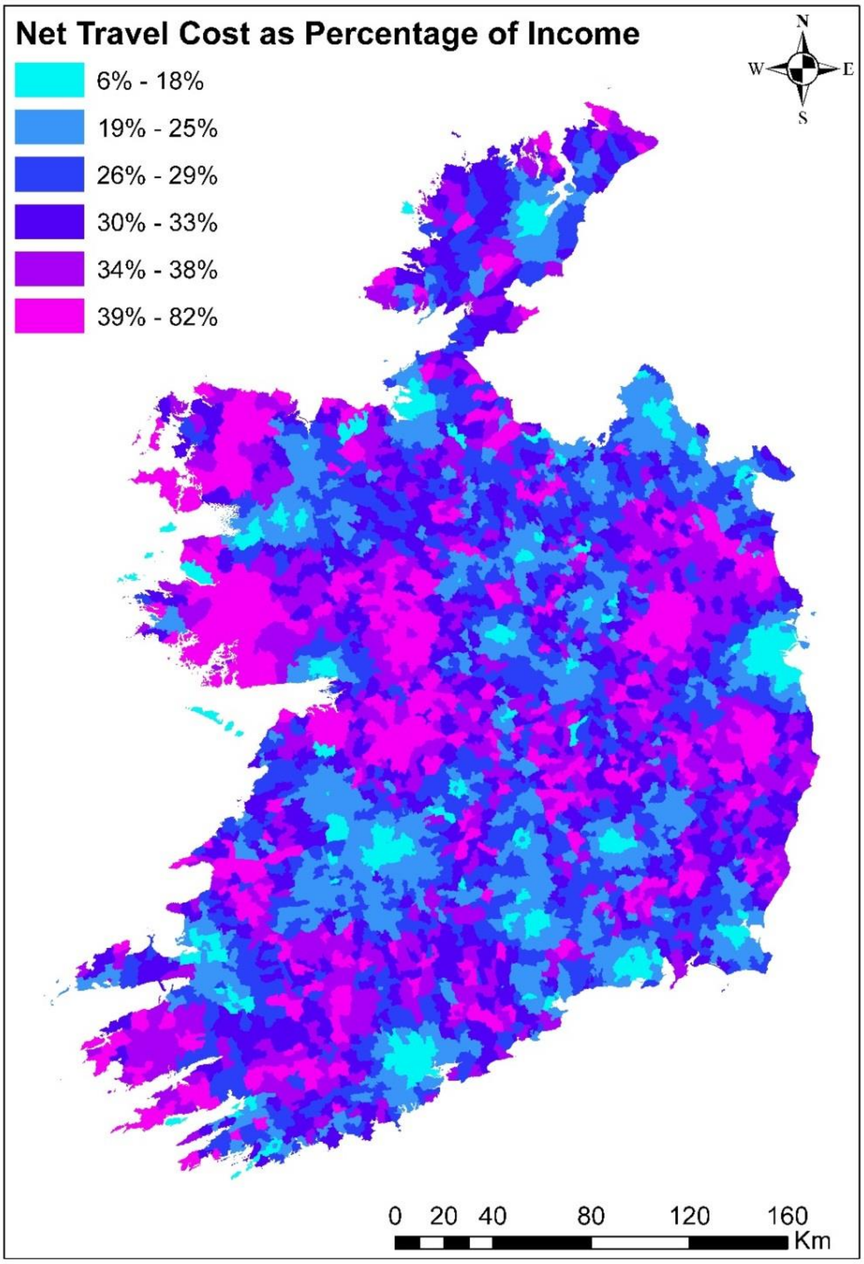
Figure 5-3: Spatial distribution of the net travel cost for Ireland



Source: SMILE, 2011

Figure 5-4 presents the net travel cost relative to employment income at the ED level. The cost of commuting as a percentage of income shows a clear spatial pattern across the GDA and the suburban areas of Galway, Cork, Limerick and Waterford. However, Dublin City shows a relatively low net travel cost as a percentage of income when compared to its commuter hinterland and other Irish cities. The highest percentage is found across the GDA, particularly to the West and North of Dublin City, with costs between 29% and 33% of employment income. This would indicate that whilst the employment profile of employees in the GDA is predominately professional (Morrissey and O'Donoghue, 2011), commuting costs represent a high share of employment income. Outside the GDA there is a clear spatial pattern in the relative cost of commuting.

Figure 5-4: Spatial distribution of the net travel cost as percentage of income in Ireland



Source: SMILE, 2011

An additional objective of this paper is to establish if lesser commuting costs impact positively on employment income relative to high commuting areas. Table 5-6 presents the average income rank, the net commuting cost as a percentage of income and the average income rank once commuting costs have been taken into account for each county in Ireland. Suburban areas of Dublin – Dun Laoghaire, Fingal and South Dublin – rank at the top in terms of income as well as counties along Dublin's commuter belt such as Wicklow and Kildare. Table 5-6 shows that both Meath and Kildare experience the largest impact of commuting relative to employment income followed by Wicklow and the Dublin City suburbs. Once commuting costs are accounted for, commuters in County Kildare move from having the 9th highest income to having the 15th highest. Commuters in County Meath, moving from the 21st highest income position to the 28th, also experience a large impact. The results reflect the high cost of commuting for individuals living in the commuting counties around Dublin.

The counties that experience the highest increase are those that are outside of the main commuting zones, with commuters in Longford and Offaly, rising 5 income positions, while commuters in a number of counties, including Tipperary North, Roscommon and Monaghan all increasing income positions. The results presented here illustrate how spatial microsimulation modelling can be used to address previously unanswered research questions, the spatial economic impact of commuting relative to income at the micro level.

Table 5-6: Income Rank and Net Commuting Cost as Percentage of Average Income by County in Ireland

County	Income Rank	Net Commuting Cost as Percentage of Average Income	Income Rank (Net)
Meath	21	33.15%	28
Laois	29	29.63%	30
Leitrim	30	27.82%	29
Kildare	9	26.78%	15
Wicklow	8	26.44%	10
Galway	26	26.18%	25
Donegal	28	25.31%	27
Cavan	27	24.86%	26
Offaly	15	24.23%	18
Roscommon	23	23.97%	23
Wexford	25	23.90%	24
Carlow	18	23.51%	20
Kerry	17	23.37%	19
Mayo	20	23.34%	21
Louth	6	22.29%	7
Longford	19	21.94%	16
Westmeath	12	21.83%	13
Tipperary Nr	10	21.72%	8
Kilkenny	24	21.35%	22
Clare	11	20.94%	9
Sligo	22	20.59%	17
Tipperary So	13	20.50%	12
Cork	14	20.15%	11
Monaghan	16	18.64%	14
Waterford	7	17.43%	6
Limerick	5	16.48%	5
Fingal	1	12.42%	3
South Dublin	4	10.12%	4
Dun Laoghaire	2	9.00%	1
Dublin City	3	7.25%	2

5.8 Discussion

During the Irish economic boom years or the so-called *Celtic Tiger* period, which took place from the mid-1990s to the mid-2000s, Ireland experienced an unprecedented rise in commuting distances within extended local labour market areas. These new commuting patterns, driven by a dispersed settlement structure and an uncontrolled property bubble that had developed over the previous five years (Fitzgerald, 2014), resulted in an increasingly uneven spatial distribution of commuting costs across Irish regions. Simultaneously, increased employment in professional and managerial posts in the GDA and other Irish cities led to higher salaries in these regions (Morrissey and O'Donoghue, 2011). This paper is concerned with the overall net effect of these developments, where higher salaries in urban areas were accepted in exchange for increased levels of commuting and urban sprawl, in particular within the GDA. This research sheds light on the impact that dispersed commuting and settlement patterns had on the spatial distribution of employment income across Ireland. To examine this, data from a spatial microsimulation model was combined with a standard travel demand model and the estimated subjective values of travel time (SVTT).

The economic crisis that hit Ireland in 2008, together with the policy developments that followed, namely the severe fiscal adjustment, have further emphasised these regional disparities. Results from this research show that while there is a relatively better provision of transport infrastructure in the GDA than in the rest of the country, the net cost of commuting in this region is significantly higher. This is particularly evident in the case of the commuter counties adjacent to Dublin City, which also present some of the highest levels of average income in the country. Overlying these results are longer-term development processes driven by complex patterns of residential and employment location and the subsequent need for longer commuting distances, which are only likely to be improved by the implementation of effective spatial planning policies.

5.9 Conclusion

Linking spatial microsimulation models to exogenous models provides a powerful tool for examining a wider range of policy questions (Morrissey et al., 2008, Smith et al., 2006, Van Leeuwen, 2010). The aim of this paper is to examine the impact of both monetary and non-monetary commuting costs on the distribution of employment income in Ireland. The lack of information on individual income within the Census of Population of Ireland, which is the only nationwide source of information on commuting patterns in Ireland, sets the rationale for the methodology presented in this paper. The paper combines a spatial microsimulation model (SMILE) with a standard travel demand model for commuting choices to present a unique dataset for Ireland that allows us to obtain the spatial distribution of the impact of commuting on employment income at the electoral division (ED) level.

Increased employment in professional and managerial posts in the GDA and other Irish cities led to higher salaries in these areas (Morrissey and O'Donoghue, 2011). At the same time, levels of commuting increased across the country, particularly in the GDA (Commins and Nolan, 2011, Vega and Reynolds-Feighan, 2009). This was accompanied by significant investments in transport infrastructure, which have primarily focused on public transport improvements in the GDA and the development of the inter-urban motorway network (Vega and Reynolds-Feighan, 2012). Incorporating data from a spatial microsimulation model within a travel demand model, it was found that while there is a relatively better provision of transport infrastructure in the GDA than in the rest of the country, the net cost of commuting in this region is significantly higher. This is particularly evident in the case of the commuter counties adjacent to Dublin City, which also present some of the highest levels of average income in the country. This paper shows that in the case of the GDA, higher income levels do not compensate for the cost commuting in these areas, which results in a relative drop in the county level income ranking. Further analysis found that other Irish cities show high net commuting costs as a percentage of income, in particular Galway City and its commuter hinterland. In contrast, the relative impact of commuting on employment income is significantly lower outside the primary commuting belts, particularly smaller towns and rural areas.

In conclusion, it is obvious that sophisticated tools are required to understand the complex dynamics that underlie labour markets and their impacts at the local and individual level. Less obvious however, is the need for sophisticated micro data detailing the residential and employment location for each employee, along with their demographic, socio-economic, labour force participation, income, resource usage, etc., profile. Combining the data created by a spatial microsimulation model within a travel demand model allows for a novel analysis of the impact of commuting on employment income at the small area level in Ireland. Understanding these impacts has implications for transport policy and transport infrastructure prioritisation at the national and regional level. The type of analysis presented in this paper and the uneven spatial distribution of the impact of commuting on employment income provide policy makers with additional tools for design and implementation of future transport infrastructure investment strategies.

Chapter 6. Spatial Distribution of Farm Viability[17]

6.1 Abstract

Significant spatial heterogeneity exists among farms. In this paper we examine farm viability using a classification concept (Frawley and Commins, 1996). A spatial microsimulation approach is used to add a spatial component to a farm micro dataset. This dataset is then linked to a spatial micro dataset of households which allows for farm and non-farm analyses within the same analysis. This dataset enables us to analyse the characteristics of the areas within which viable farms exist in addition to the farms themselves. This paper aims to show that there exist spatial differences in viability and to identify the drivers. The location in which a farm is situated will likely determine which sub-sector they belong to. The more profitable sub-sectors tend to be clustered in the same location. In addition to the spatial heterogeneity in farm income sources, there is also significant heterogeneity in employment, types of employment and access to labour markets. The results show how the different viability measures are concentrated in a particular area. Viable farms in the south, sustainable farms in the midlands and west and vulnerable farms in the north-west. The areas with higher proportions of unsustainable farms tend to be in areas outside the commuting zones and are characterised by having high levels of unemployment and low average skills. Access to local labour markets is a major determining factor in whether an area is a sustainable or vulnerable farming area.

6.2 Introduction

Von Thünen (1826) was one of the first to recognise the interaction between spatial analysis and the economy, in Von Thunen's model land rent is a function of yield per unit of land and transport costs (which is a function of distance). This land rent will be a function of the level of competitive advantage in using the land productively (Ricardo, 1821). This recognises the level of spatial differences that exist in an economy. Launhardt (1885) & Weber (1909) adopted a least cost theory approach to industrial location. Firms will locate where materials, labour and transportation costs are all minimized. The growth and increasing importance of globalisation saw the emergence of the "new economic geography" (NEG) (Krugman, 1998). The NEG aids in

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explaining the uneven spatial development that exists. Given the growing trends of urbanisation we will face many challenges. Lower transport and communication costs are driving economic development in rural areas. Limited supply of land means it must be used optimally (Henderson, 1974). Agglomeration economies cause industry to cluster together. Aspects such as lower transport costs, economies of scale and market size (Krugman, 1991). The NEG uses a core periphery model. This will lead to a concentration in an area which can increase land rents making it unaffordable for residential and causing urban sprawl (Brueckner, 2000). Expanding cities also encroach onto agricultural land causing pressures. In addition to this pressure on land, cities also impact on the viability of farms through their local labour markets. Higher incomes in cities are more attractive compared to potential incomes from farming. More recently in advanced economies it has become more difficult to spot industry concentrations as they have become more subtle. Tangible forces of NEG are also not as powerful in explaining localisation. The no-dormitive-principles are more difficult to hold with invisible external economies such as information spillovers being more relevant compared to transport costs (Krugman, 2011). Technological advances have made some of these transport costs, costless in some industries. Even without physical differences between areas there are differences that can arise due to these spillovers, thick market effects or linkages between firms (Kanbur and Venables, 2003).

One aspect of welfare which incorporates both housing and commuting elements, is access to local labour markets (Van Ommeren et al., 1999b, Dohmen, 2005). The spatial mismatch hypothesis (Kain, 1992), was used to explain high rates of unemployment among African Americans, largely due to geographical barriers to access concentrate job markets. Commuting distance to job opportunities will impact on the spatial distribution of employment (Rogers, 1997). Workers can be sorted in both the skill space and geographical space in a similar fashion (Brueckner et al., 2002). Low access and low availability of high skilled jobs can lead to a “low-skill, bad-job trap”, where there is a low incentive for workers to upskill and for firms to offer high skill jobs (Snower, 1994). High wages tend to be found where high skill workers concentrate in dense local labour markets (Combes et al., 2008). These thick labour markets will increase efficiency in matching worker skills to jobs (Krugman, 1998). Owner occupier, high skilled workers are more likely to move to find employment as the income they forgo when unemployed exceeds unemployment benefits and moving costs. Higher moving costs and lower mobility can raise unemployment (Dohmen, 2005). Those who are home owners are less likely to move residence for work, while job mobility is found to increase with commuting distance (Van Ommeren et al., 1999b).

Workers in rural areas are more likely to have greater commute times and likely to be net senders of workers to urban areas (Hazans, 2004). These local labour markets will have an impact on the economic viability of farming. A large percentage of farmers engage in off-farm employment (Kinsella et al., 2000). Due to the high reliance of agriculture on off-farm employment and subsidies (O'Donoghue, 2013), economically viable farming is influenced by spatial environment attributes and local labour markets. These spatial environment attributes, such as soil quality will impact on farm productivity with areas having distinct advantages (Frawley and Commins, 1996). As farming assets are largely immobile, farmers cannot simply move to have greater access to local labour markets. Spatial access to labour markets will therefore influence farm viability through a farmer's ability to find off-farm employment. The farmer's skill level is also likely to influence their probability of finding employment. In the OECD rural areas make up 75% of the land and 25% of the population. There is a growing need to redefine what we mean by rural. Rural varies between areas that are close to urban areas which are more resilient compared to remote rural areas which are vulnerable to economic conditions. Rural policy 3.0 (OECD, 2016d) policy framework moves beyond farming and subsidising specific sectors towards making rural areas more competitive. This new approach also recognises the fact that there are different types of rural areas. It recognises the opportunities that exist in rural areas outside of agriculture. Rural areas with a higher quality of life but lower wages can attract and hold onto workers and their families. The rural economy is hugely important to Ireland with over 50% of GDP generated in rural areas. Ireland also has the largest rural population in the OECD with over 60% of the population living in a rural area (OECD, 2016c). Teljeur and Kelly (2008) found a similar figure with ~65% not living in a city. ~31% of the population was classified as living in a rural area with 11.3% of that figure designated remote rural. These remote rural areas are heavily reliant on agriculture for employment. The biggest challenge for rural development will be in these areas which are not close to an urban centre and so do not have access to a large labour market. Given the high proportion of early school leavers these areas have a low skill base. If an area is simply defined as being rural or urban, we miss a lot of the complexities. Although these remote rural areas face a number of challenges, they also have a number of opportunities such as being able to offer unique environments to firms and employees

(OECD, 2016b). Innovative approaches will have to be taken to increase growth in these regions and areas.

Policy Context

A great deal of spatial heterogeneity exists in agriculture in Ireland (Crowley et al., 2008). The more profitable sub-sectors tend to be clustered in the same location. The majority of the best quality land is located in the South and East of the country and the poorer land in the North and West (Frawley and Commins, 1996). Within these South and Eastern regions, the most profitable farming sectors dairy and tillage are located. Low margin beef and sheep sectors are concentrated in the Midlands, North and West regions. Understanding this spatial heterogeneity that exists in Irish agriculture can help in targeting agricultural subsidies more efficiently. In addition to the spatial heterogeneity in farm income sources, there is also significant heterogeneity in employment, types of employment and access to labour markets. Acknowledging these structural differences can lead to better policy interventions (O’Donoghue, 2013).

The agricultural sector in Ireland remains heavily reliant on farm subsidies (O’Donoghue and Hennessy, 2014), which can account for as much as 65% of income. Without these subsidies from the Common Agricultural Policy (CAP) very few farms remain viable (O’Donoghue, 2013). Hennessy (2004) and Frawley and Commins (1996), define a useful farm classification called viability. A farm is classified as economically viable if it has the capacity to remunerate family labour at the average agricultural wage, together with a return of 5 per cent on non-land assets. A farm is considered sustainable if they are not viable, but have off-farm employment. The residual category is neither viable nor have off-farm employment and is thus unlikely to be sustainable in the long term. We build upon the analysis conducted in O’Donoghue (2013) by examining the characteristics of areas by viability classification. We also use hot-spot analysis to identity clusters of farm viability, sustainability and vulnerability.

The pull factor of high off-farm incomes, and push factor of de-coupled payments, lead to a high of 58% of farm households having at least one off-farm job in 2008. Off-farm income however is of great importance to Irish agriculture. As much as 40% of farms are only made sustainable by having off-farm income (Behan et al., 2007). This access to off-farm employment however is not homogenous in nature. The presences of local labour markets play an important role. The size of the labour market and level of income will depend upon location. Incomes tend to be higher in urban areas. Although advances in technology have greatly reduced communication costs, industry still tends to cluster together. The possibility now exists to work remotely in rural areas, which has great potential for these areas. It is worth noting however that uniform economy wide polices designed for urban will not have the same effect on rural areas where a more tailored approach is required. Innovation is needed in the creation of rural policies (OECD, 2014a).

6.3 Methodology

In order to estimate spatially farm level income and the household income, two separate spatial microsimulation models are developed; one for farms and one for households. The former links the National Farm Survey (micro data) to the Census of Agriculture and the latter links micro household income data (the Living in Ireland Survey) with the Census of Population. A statistical matching algorithm that generates a micro dataset with the characteristics of the spatial control dataset is utilised in our model (Farrell, O'Donoghue and Morrissey, 2011). While the household model has aggregate farm income, it does not contain detailed farm level income required for more in depth analysis. For this we need to match the two spatial datasets. This step requires statistical matching. Due to the relatively few overlapping variables between the two datasets, we utilise a Grade Correspondence method a commonly used technique, where farms are matched on the rank of income (Decoster et al., 2009).

Microsimulation

As identified above agricultural policy in Europe and in Ireland is increasingly taking a territorial dimension, with an increasing focus on place. Given the very heterogeneous characteristics of different locations due to different environmental conditions, access to markets and population distribution, it is important therefore to have spatial data to inform policy debate and discussions. Secondly within these spatially heterogeneous areas, there is a significant degree of heterogeneity across different farms. Any policy analysis such as the creation of sustainability indicators needs to take this variability into account.

Given the focus on agricultural activity, the environment, social structures and welfare enhancing policies underpinning rural sustainability, to develop sustainability indicators suitable for the analysis of agricultural and rural development policies, we therefore require spatial micro data with the following attributes:

- The distribution of agricultural activity and its economic impact
- The relative contribution of farming and non-farming incomes within farm households and across other households
- The environmental characteristics of agricultural activity (nitrogen use)
- The distribution of demographic characteristics

Each of the three sustainability indicator categories is examined; environmental, economic and social. In the environmental case we focus on nitrogen levels and usage. This will incorporate the spatial elements of soil type and weather. You would expect areas with poorer soil quality to use more nitrogen on their land. In the economic case we look at whether a farm is viable or not. This will be impacted by access to markets, local labour markets as well as farm size.

Data

The data we require in relation to farms comes from the National Farm Survey (NFS). contains detail farm enterprise level micro data on farm activities (See Connolly et al. (2009)). However this data is only available at the national level and only spatially representative to the NUTS3 level. A range of household surveys including the Household Budget Survey (HBS), the Living in Ireland Survey (LII) and the Survey of Income and Living Conditions (SILC) contain the distribution of incomes, labour market and demographic characteristics, but again are only representative at the national level and with limited agricultural data. The Census of Population Small Area Statistics contain spatially disaggregated data (3400 divisions) on economic activity and demographic characteristics, but is not available at the micro level and does not contain incomes. Similarly the Census of Agriculture is available at this spatially disaggregated level, but again has the same flaws as the Census of Population. There are good spatial environmental characteristics available in the Teagasc spatial data archive, however this GIS based data is not linked to activity. Therefore, unfortunately no single dataset provides such a range of data, either at the national level or particularly at the spatial level.

Spatial microsimulation which is a methodology designed link using statistical methods data to produce data that can be used to analyse the spatial implications of economic development and policy changes (Holm et al., 1996), seems ideal for this purpose. A microsimulation model uses microdata on individuals, farms, firms, etc. to build large-scale data sets based on the real-life attributes of individuals, farms or firms and then simulates the effect of changes in policy on each of these units. By permitting analysis at the individual level, spatial microsimulation methods allow one to assess both between location variation and within location variation across farms and households (Ballas et al., 2005a, Holm et al., 1996). These models are flexible in terms of spatial scale in that they can be re-aggregated or disaggregated. For example, the model developed in this paper can be aggregated to counties (by ED) or regions (by province). Third, spatial microsimulation models store data efficiently as lists; the lists generally consisting of unidentifiable units with associated characteristics obtained as mentioned above, from a survey or census.

Model Construction

In order to create a spatially microsimulated dataset for use in the development of sustainability indicators, we need to undertake the following steps:

- Create a spatial micro dataset of farms, containing the spatial distribution of agricultural activity and incomes

- Create a spatial micro dataset of households, containing the spatial distribution of other economic activity and incomes, consistent with spatial demographic characteristics

- Link the two spatial datasets via statistical matching to allow for farm and non-farm analyses in the same analysis

- Link the generated spatial micro dataset to GIS layers of environmental attributes and rural services.

- Simulate agricultural outputs that may impact upon the environment such as Nitrogen compound production and Methane production.

Spatial Distribution of Rural Households and Farm Enterprises

Fundamental to the creation of a spatial micro dataset using microsimulation techniques is a statistical matching algorithm that generates a micro dataset with the characteristics of the spatial control dataset. Our objective is to undertake analyses based upon the spatial distribution of both agricultural income and activity and of wider household incomes. As no single set of data (either at micro or spatial scale) contains detailed farm and household information, we develop two separate models; one for farms and one for households. The former links the National Farm Survey to the Census of Agriculture and the latter links micro household income data (the Living in Ireland Survey) with the Census of Population.

A number of methods exist to undertake the statistical matching exercise. These include iterative proportional fitting, simulated annealing, deterministic reweighting, generalised regression reweighting and quota sampling (see O'Donoghue et al. (2013a) for a description of these methods).

Various stages of the model development have used different methods. The first variant focusing on population demographic issues (Ballas et al., 2006b) used iterative proportional fitting to generate the model. Hynes et al. (2009a) developed a farm level model using simulated annealing, while Morrissey et al. (2010) developed a household level model for rural service provision analysis, again using simulated annealing. While simulated annealing is reasonably accurate, it imposes significant computational constraints due to the length of time required to undertake the match. Farrell et al. (2010) have developed a method based upon simulated annealing that samples data from a micro dataset in accordance with “quotas” provided by spatial control data from the census, using randomised sampling without replacement to improve the computational speed of selection.

Table 6-1 describes the match variables. These variables meet the requirement of being available in both the sampling datasets (NFS and LII) and in the spatial constraint data (Census of Agriculture and Census of Population respectively). Given the computational cost of adding extra variables, which increases at a non-linear rate, we are limited in the number of constraints that can be used. A particular feature of the method used in this paper is that multiple units of analysis can be used, so that individual constraints such as the number of people by education can be combined with a household unit of analysis in the sampled dataset. This allows sub-levels such as individual and family or farm sub-enterprise to remain consistent with the higher level unit such as household or farm. Morrissey and O'Donoghue (2013) have found that the method almost perfectly replicates the control totals described in table 6-1 and performs satisfactorily when compared against high level external validation totals not used in the creation of the model.

Table 6-1: Model's Baseline Variables, Categories and their Dataset Source

	Sample Data	**Census Data**
Farm Level		
Farm Size (6 groups)	NFS	Census Of Agriculture
Farm System (7 groups)	NFS	Census Of Agriculture
Dominant Soil Type (5 classes from wide use range to soils where the agricultural potential is very restricted).	NFS	Soil Map of Ireland
Number of Farms in each ED	-	Census Of Agriculture
Household Level		
Number of People by Age Group and Sex	LII	Census of Population
Number of People by Education Level	LII	Census of Population
Number of Households in each ED	-	Census of Population
Is a Farming Household	LII	Census Of Agriculture

Spatial Distribution of Farming and Non-Farming Income

While this method produces a good match for matching variables and high-level validation comparisons (county poverty rates), we find the assumption of conditional independence required in statistical matching is broken for many non-match variables. Essentially this results from the fact that the variables used for the statistical matching do not capture all spatial heterogeneity. In other words the spatial variability of variables such as employment status depends upon other characteristics than the spatial pattern of age-sex-education. Examples may include the spatial pattern of occupation or characteristics associated with local labour markets, e.g. more professionals living closer to cities.

One alternative is to increase the number of constraint variables, to for example include the number of workers within an ED as a constraint. While this is feasible, the computational cost is quite high given the fact that the match needs to take place for 3400 divisions. In any case also, the same issue will arise for lower order variables, so that while the proportion of people in-work may be correct after a match, it would be less likely to capture the spatial pattern of having a greater proportion of self-employed within the division. Instead we utilise an alternative method drawing upon our experience in dynamic microsimulation modelling (See O'Donoghue (2001))

This mechanism is based around model calibration. The objective of calibrating a spatial microsimulation model is to ensure that the simulated output matches exogenous totals at varying levels of spatial disaggregation (Bækgaard, 2002). SMILE incorporates a system of regressions with the non-matched variables as dependent variables, combined with an array of alignment processes (See O'Donoghue et al. (2013a)). There are a number of different alignment processes one may use and the choice of process depends on the type of data outputted from the microsimulation model and the data type of the exogenous 'target' data. In our model we utilise three types of alignment for binary discrete data, discrete data with more than two choices and continuous data.

Average county income by income source are calibrated to county level national accounts. Due to definitional differences, which if adjusted for can seriously affect the distributional properties of the data, instead of scaling average income by source to the national accounts total, we adjust instead by the ratio of average income by source to the national average (Morrissey and O'Donoghue, 2013). Thus by and large we maintain the same distribution properties of the underlying income data. While these are well known under reporting of particular incomes such as capital income and self-employment income (see Atkinson et al. (1995)), income surveys are typically not adjusted to account for these issues.

The typical measure used for welfare analysis is disposable income, defined as market income plus benefits minus taxes. We utilise a tax-benefit routine described in O'Donoghue et al. (2013b) to generate measures of disposable income.

Linking Household and Farm Models

With our focus on rural development, we need to undertake an integrated farm enterprise-household analysis. While the household model has aggregate farm income, it does not contain farm level detail required to, for example model environmental outcomes. For this we need to match the two spatial datasets. This is done in two stages. Firstly within the household model, we differentiate between having farm income and where farming is the dominant employment status. This is because of the high prevalence of off-farm employment in Ireland where over 50% of farmers have an off-farm job (See Connolly et al. (2009)). Thus many individuals with farm income will have a main employment status that is not farming. To ensure consistency between the models, we use the number of farms generated within the farm microsimulation model as a calibration total for the number of farm households within each district. We utilise the continuous alignment function to produce an estimate of total household farm income. The spatial farm dataset also contains a measure of household farm income.

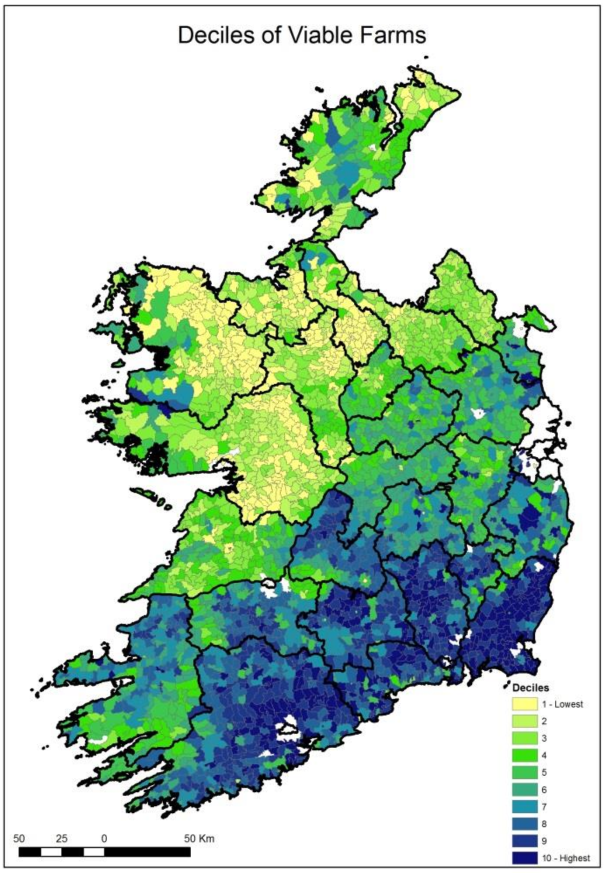
The last step requires us to link the farm households in the household dataset with a total value of farm income with the farm households in the farm dataset with nearly 2000 technical, input and output variables including total farm income. This step requires statistical matching. There are a number of different possible options in statistically matching this data outlined in Decoster et al. (2009). However due to the relatively few overlapping variables between the two datasets, the parametric and non-parametric regression methods as well as the minimum distance methods are not suitable. Therefore we utilise a Grade Correspondence method which is used quite frequently in the literature, where farms are matched on the rank of income. As the farm numbers in the household dataset have been calibrated to the number in farm dataset, both models thus have the identical number of farms per division. We therefore merge on the rank of farm incomes, replacing the farm incomes from the survey with the farm incomes from the farm survey which are consistent with the underlying farm structure variables. Although not examined here, this matched dataset can be used for example to get the distributive impact in terms of household income of farm subsidies targeted at specific enterprises such as the Beef Suckler Welfare Scheme or environmental instruments such as carbon taxes and water regulations.

We also make use of river catchments data from the WFD to estimate nitrogen use by area. Nitrogen use can be used as a proxy for both soil quality and weather. Using GIS techniques we identify which EDs are situated in a particular river catchment. The data for that river catchment is then assigned to that ED. Where EDs overlap with the river catchment boundary, the ED is assigned to the river catchment which contains the majority of its area.

At the end of this process we are left with a spatial rich dataset which contains farm, individual, environmental, demographic, spatial and economic data at a spatially disaggregated scale, ED level in this case. This data enables us to firstly categorise farms in one of three categories, viable, sustainable and not viable or sustainable. Using these categories we can then identify any particular spatial patterns to the results and whether in fact space can determine whether a farm is viable or not.

Figures 6-1, 6-2 and 6-3 display each of the three viability measures divided into deciles with blue having the highest levels and yellow having the lowest. Figure 6-1 is the spatial distribution of viable farms. There is a clear north/south divide with the most viable farming areas located in the south where the soil is of better quality compared to the north. Viable farming areas follow the Dundalk to Limerick line as was found in Frawley and Commins (1996).

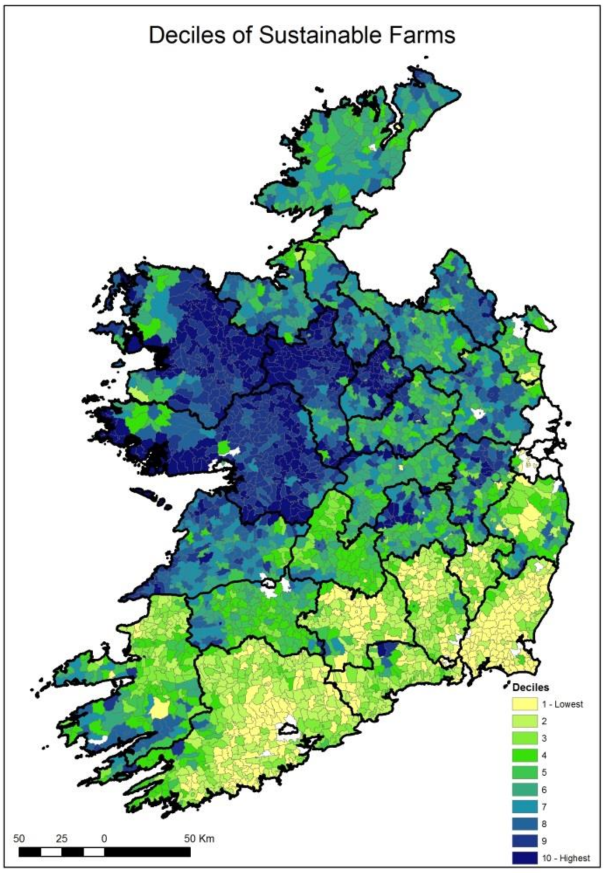
Figure 6-1: Deciles of Viable Farms



Source: SMILE

In figure 6-2 the most sustainable farming areas are located mainly above the Dundalk to Limerick line. There is a large concentration in the west of the country in the province of Connacht.

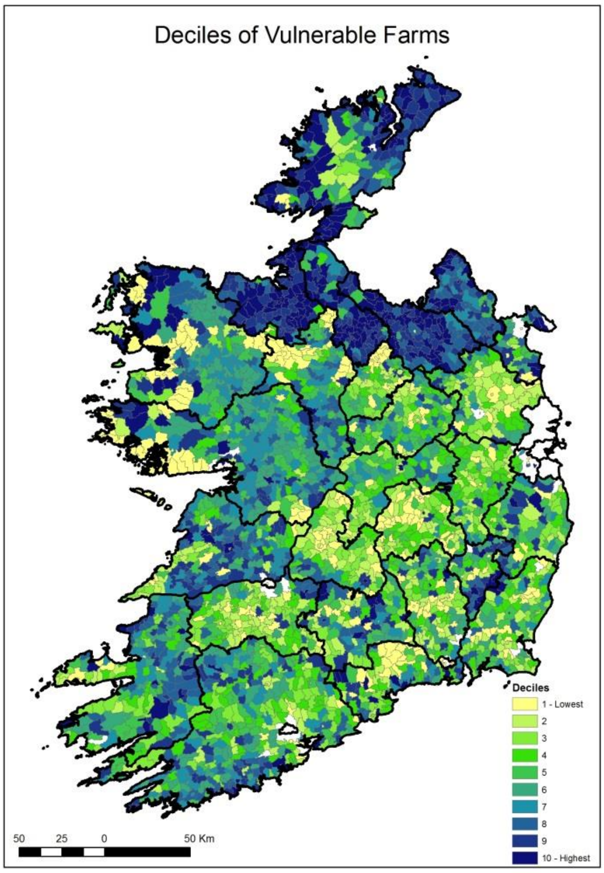
Figure 6-2: Deciles of Sustainable Farms



Source: SMILE

The areas with the highest levels of vulnerability as shown in Figure 6-3 are located in the north-west and border region with pockets located along the western coast. After examining the three figures the viability measures are concentrated in a particular region; viable in the south (below Dundalk to Limerick line), sustainable in the mid-west and vulnerable in the north-west.

Figure 6-3: Deciles of Vulnerable Farms



Source: SMILE

6.4 Results

For our results we have divided EDs into population weighted quintiles based on the percentage of farms in an ED that are of a particular farm viability measure. Table 6-2 shows the results of this analysis. Comparing the areas that are classified are being vulnerable versus the areas that are viable, measures of employment, unemployment and distance show the largest difference. Areas which are vulnerable tend to have higher levels of unemployment, lower levels of employment, third level education and those working in the professional classes. They are also more isolated being further away from both a city and rail station and have a low population density. The lower levels of organic nitrogen per hectare and livestock units per hectare would suggest that they are farming less intensively. Observing data from 2016 shows this pattern has not changed over the past five years. Levels of employment, third level education and unemployment rate all remaining worse off compared to the viable areas. The areas classified as sustainable have levels of employment and unemployment in between that of vulnerable and viable farms. Although not performing as well as viable areas, they have distinct advantages over that of the vulnerable areas in that they are not as isolated. The lower distance measures and higher population density would suggest they are closer to centres of economic activity. Since 2011 they have also performed better than vulnerable areas. A slight gap has emerged since 2011 between sustainable and vulnerable areas. These advantages have perhaps played a role in improving the economic prospects of these areas since the great recession.

Table 6-2: Summary Statistics of Viability Measure for Highest Quintile (Q5)

	2011			2016		
Q5	Vulnerable	Sustainable	Viable	Vulnerable	Sustainable	Viable
Old Age Dep.	22%	23%	20%	27%	27%	23%
Employ. Rate	58%	60%	61%	65%	66%	66%
Unemp. Rate	13%	12%	11%	9%	8%	7%
Unemp. Rate (Male)	18%	17%	16%	11%	10%	9%
Profess.	49%	51%	53%	51%	52%	56%
Manual	30%	29%	28%	28%	28%	26%
Unskilled	21%	21%	19%	21%	20%	18%
Education Rate	32%	32%	36%	36%	36%	40%
% Mortgage (hh's)	34%	35%	39%	31%	32%	35%
% Own Occ. (hh's)	48%	49%	45%	49%	51%	46%
Disp. Income (hh)	20,092	20,249	21,144			
Median Pop. Density	25	20	29	25	20	30
LU per hec.	1.05	1.06	1.44	1.05	1.07	1.45
Organic N per hec.	88	90	118	89	90	119
Farm (hh's)	28	29	28	27	28	27
Distance to:						
City (km)	86	56	34	87	56	33
Rail station (km)	31	14	14	31	14	14
Coast (km)	26	36	24	26	36	24

To further disaggregate our results we perform a cross-tabulation between the quintiles of viable and vulnerable areas. This gives us an idea of the level of overlap between areas. Unsurprisingly, 50% of the vulnerable areas in Q5 are in Q1 for the viable areas.

It is these areas that are in most need of development, they are characterised by having high levels of vulnerable farms and at the same time farming is not viable in these areas.

Table 6-3: Cross-Tab of Viable & Vulnerable Quintiles (% of population)

	Vulnerable						
		1	2	3	4	5	
	1	9%	3%	19%	19%	50%	100%
	2	13%	15%	14%	29%	29%	100%
Viable	3	20%	31%	20%	18%	10%	100%
	4	19%	25%	26%	20%	9%	100%
	5	38%	26%	22%	13%	1%	100%
		100%	100%	100%	100%	100%	

In Table 6-3, vulnerable quintiles are sub-divided based on their unemployment rate. Focusing on the areas with the highest levels of unemployment, they largely belong to Quintiles 1 & 5 of the vulnerable areas. There is a need for retraining in the areas belonging to Q1. Although the unemployment rate is high, the majority of farms in these areas are either viable or sustainable which suggests that there are job opportunities in these areas.

Table 6-4: Cross-Tab of Vulnerability Quintiles and Unemployment

		Low		Vulnerability		High	
		1	2	3	4	5	Pop Share
Low	1	28%	42%	40%	36%	21%	33%
Unemployment	2	27%	31%	36%	38%	36%	33%
High	3	45%	26%	24%	26%	44%	33%
		100%	100%	100%	100%	100%	

Table 6-5 shows the distance statistics of these areas. Taking only the areas with the highest levels of unemployment (group 3); we examine vulnerable quintiles 1 & 5 and further break down Q5 so that only areas with little or no viable farms are examined. Comparing Vulnerable Q5 & Q1 the distance measures highlight the contrast in isolated. When we examine the vulnerable areas with no viable farms, the distance measures increase. The areas with high vulnerability and unemployment cannot benefit from the concentrated labour markets found in cities when looking for employment.

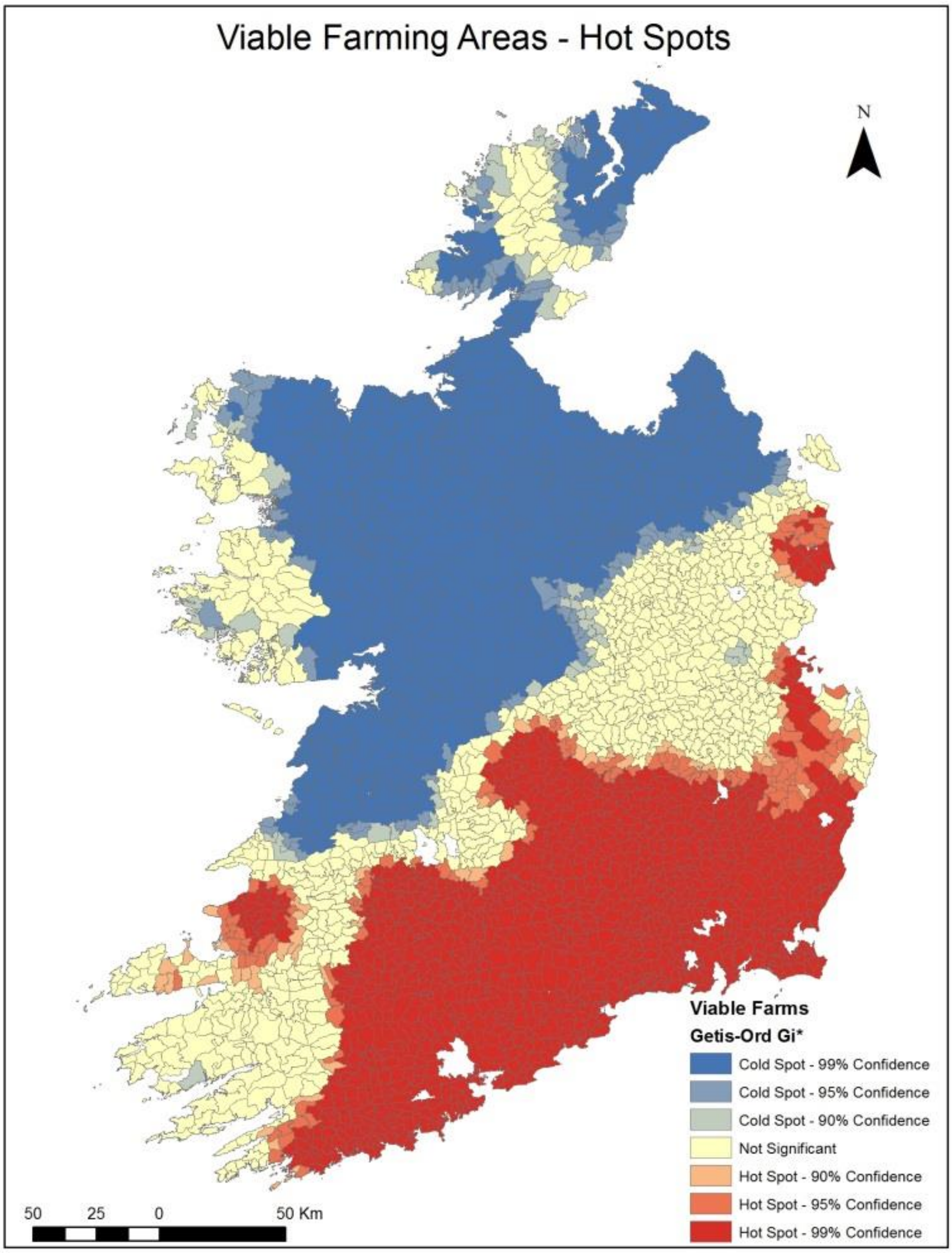
Table 6-5: Peripherality of Areas with Highest Levels of Unemployment

Highest Levels of Unemployment	Vulnerable Q5	Vulnerable Q1	Vulnerable Q5 & Viability Q1
Dist. to City (km)	113	56	126
Dist. to Rail station (km)	46	19	49
Dist. to Coast (km)	21	32	22

To identify the location of these areas we utilise the optimised hot-spot analysis function in ArcMap. This tool identifies statistically significant spatial clusters of high values (hot spots) and low values (cold spots). The Getis-Ord Gi* identifies statistically significant hot and cold spots, corrected for multiple testing and spatial dependence using the False Discovery Rate (FDR) correction method. The results for each of the three viability measures are shown in figures 6-4, 6-6 & 6-7.

Figure 6-4 shows the hotspots of viable farming areas. This illustrates a very interesting pattern as it follows the Commins-Frawley (Frawley and Commins, 1996) line (Dundalk to Limerick). Anything below this line is likely to be a viable farming area. These areas are classified by having the best and most fertile soils and so have a distinct natural advantage over other regions. In terms of output the most productive farms tend to be located here as they can benefit from having fertile land.

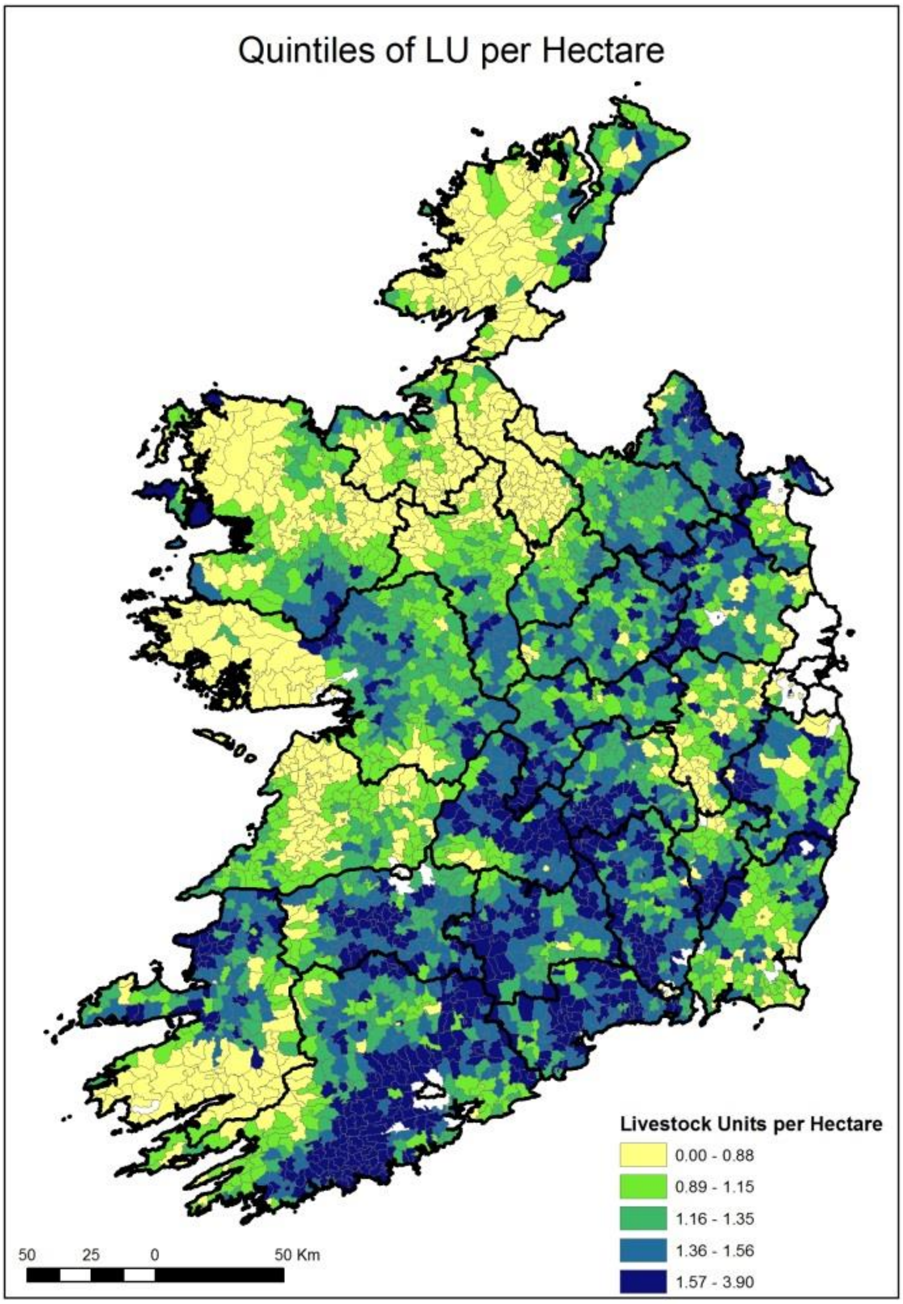
Figure 6-4: Hotspots of Viable Farming Areas



Source: SMILE

From Figure 6-5 we can see that the most intensive farming areas, using livestock units per hectare as a proxy, are located in these viable farming areas. The high productivity of land enables farmers in these areas to farm more intensively compared to areas in the north and west where soil quality is not as good.

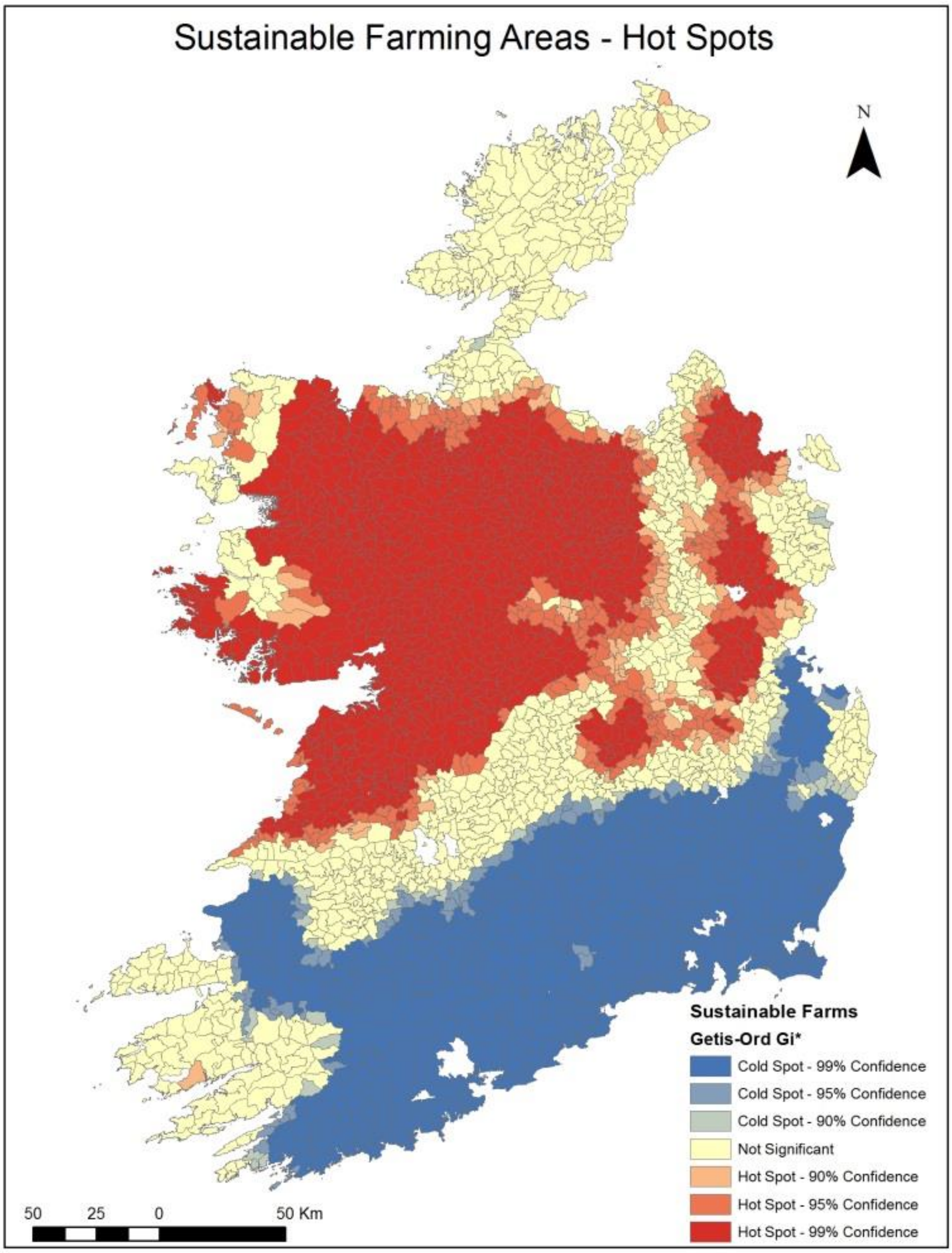
Figure 6-5: Quintiles of Livestock Units per Hectare



Source: SMILE, NFS

Figure 6-6 shows the hotspots of sustainable farming areas. The highest levels of sustainable farming are in the west, midlands and eastern regions particularly around Dublin. The access to off-farm employment, results in these areas being classified sustainable as opposed to vulnerable. This map however highlights the vulnerability of farming in these areas to shocks in the economy. Any downturn in the economy and loss of employment could result in many of these areas becoming predominantly vulnerable farming areas. The off-farm employment can almost be considered as subsidising farming in these areas.

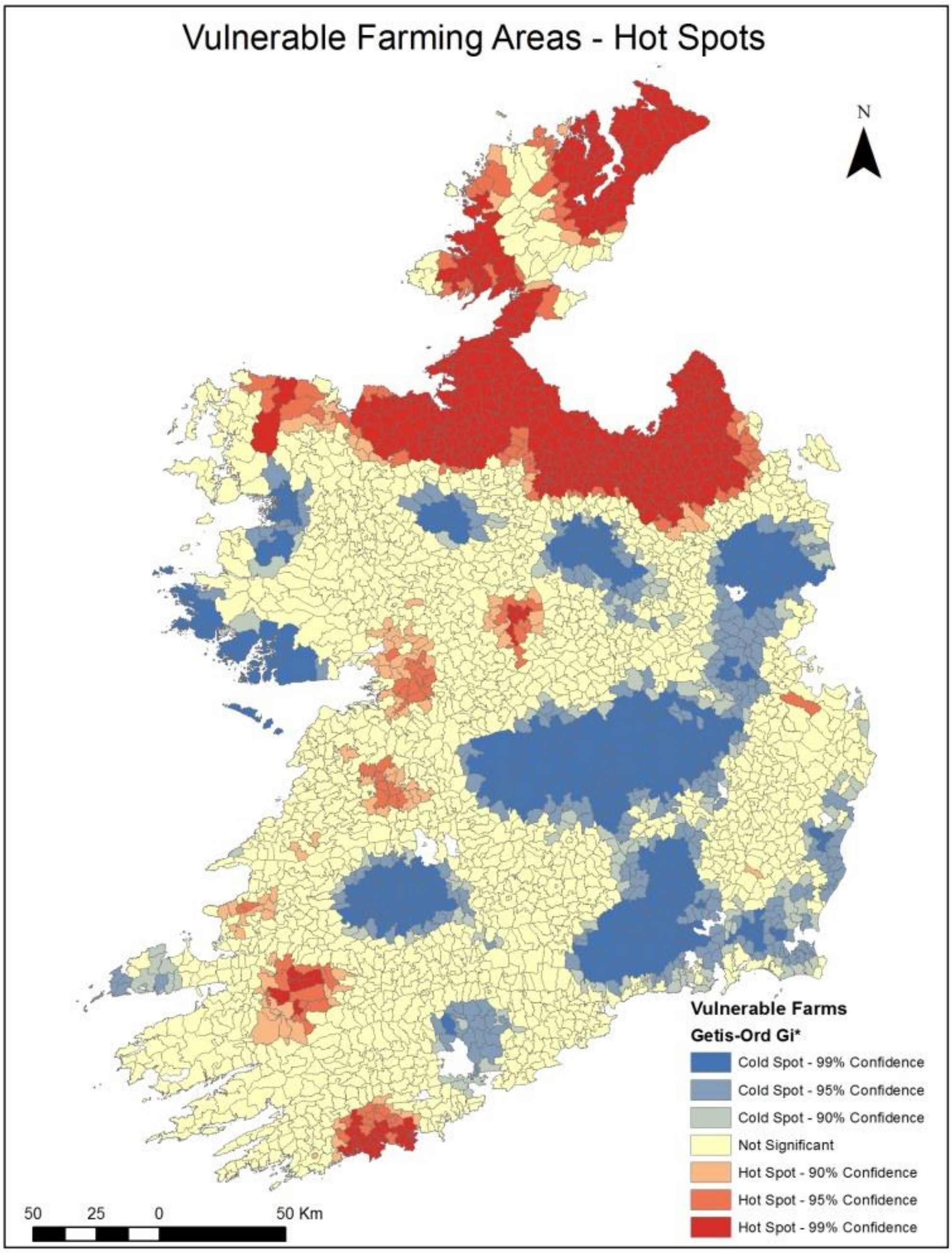
Figure 6-6: Hotspots of Sustainable Farming Areas



Source: SMILE

Finally from figure 6-7 we can see that the majority of vulnerable farming areas are located in the north-west region. There are however a number of smaller pockets close to the west and south coast which should not be ignored.

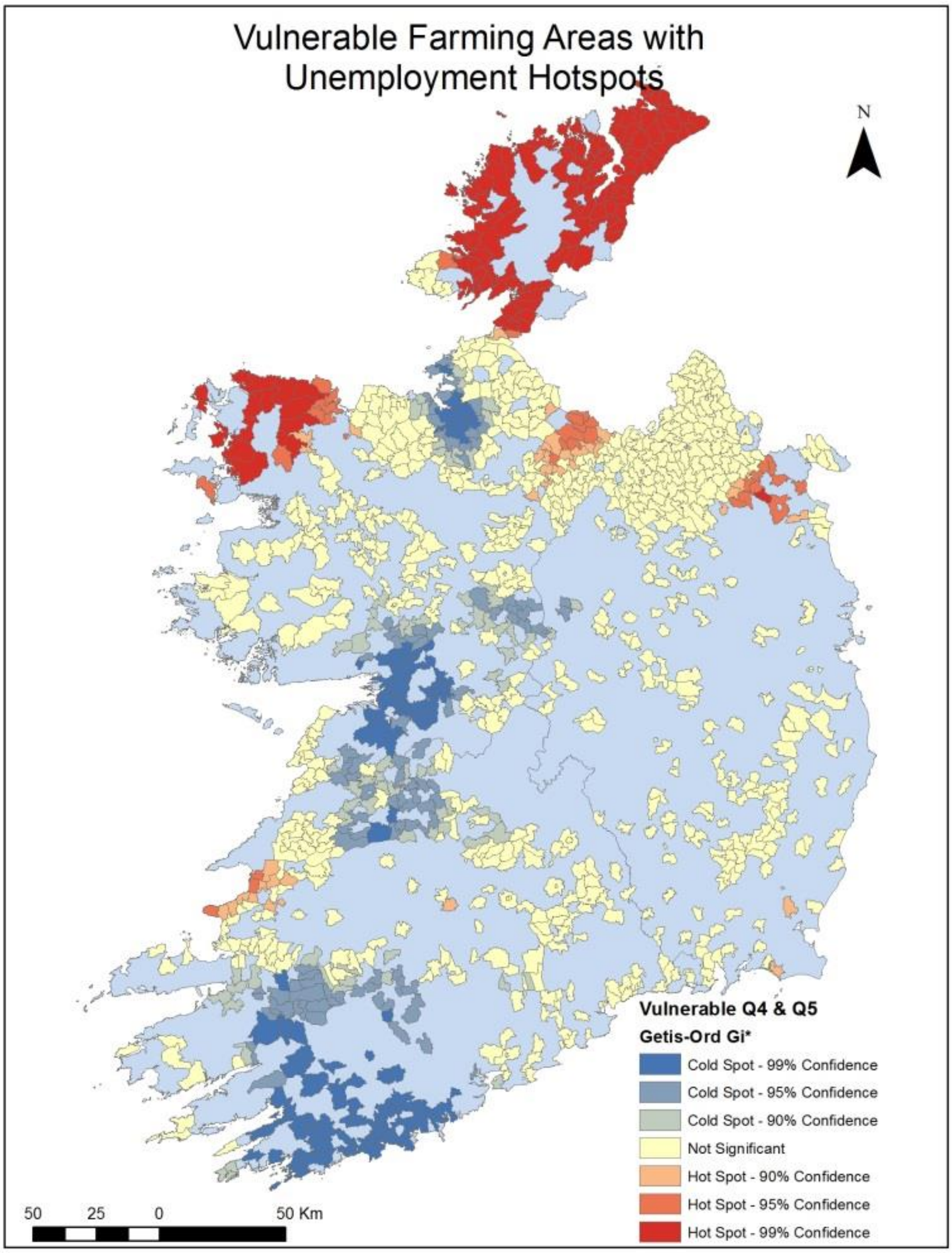
Figure 6-7: Hotspots of Vulnerable Farming Areas



Source: SMILE

Using our analysis from earlier we focus only on the areas in Q5 vulnerable that had high levels of unemployment. We can see from figure 6-8 that areas of vulnerability close to urban centres are less likely to experience high levels of unemployment. Their close proximity to major towns and cities results in better employment opportunities compared to those in the north-west. Despite the north-west being close to Derry city, the high levels of unemployment there, results in less job opportunities compared to other major cities such as Dublin, Galway or Cork. It is clear that local labour markets are having an impact on employment opportunities in these areas. The areas highlighted in red are particularly economically vulnerable. In addition to farming in these areas not being viable, there is also high unemployment and low job opportunities.

Figure 6-8: Hotspots of Vulnerable Farming Areas with High Levels of Unemployment



Source: SMILE

6.5 Conclusion

Spatial microsimulation and the creation of the three farm viability measures have enabled us to examine the drivers and barriers to rural development. We found that while there are still a large number of farms that can generate viable returns, the returns from farming provide only a relatively modest income. These results are very sensitive to the presence of agricultural subsidies. A large proportion of farming is classified sustainable; this is largely due to the availability of off-farm employment. Local labour markets play a major role in the viability of farming. The recent economic downturn resulted in reduced employment, particularly in areas where farmers traditionally find work such as construction. This poses serious risks for sustainability. Lastly, the areas with higher proportions of unsustainable farms tend to be in areas outside the commuting zones which even during economically prosperous years pose demands for rural development policy to improve the economic sustainability of these areas.

The maps of the three measures show how each of the three measures is concentrated in a particular area. Viable farms in the south, sustainable farms in the midlands and west and vulnerable farms in the north-west. It is these vulnerable areas that are of most concern. Outcomes for the areas with high levels of unemployment have improved very little since 2016. These areas are in most need of targeted resources and in particular rural development funding. This analysis also raises a question about whether it is reasonable to subsidise the areas with high levels of viable farms given that they benefit from distinct natural advantages such as superior soil quality. The problems for the vulnerable areas are largely structural, they are isolated and individuals cannot readily access off-farm employment. The large distance from these areas to a city highlights this. There are also other disadvantages to this rural isolation such as limited access to 3rd level education and health services. These areas are being left behind and although unemployment decreased since 2011, it remains above the national average.

It is particularly the areas which have the highest levels of unemployment that are of greatest concern. Unlike in the areas of high unemployment not classified as vulnerable, workers cannot simply be re-trained and re-skilled. Very often these areas are coming from a low base of education and training. ~50% of individuals are unskilled workers. These areas are particularly vulnerable. The lack of growth in these areas can also have knock-on generational effects. The lack of opportunities whether in farming or off-farm employment, acts as a disincentive for future generations to remain in these areas and increase the levels of outward migration. The low skills base of these areas makes it difficult to attract high-skilled jobs to these areas. Rural development policy should be aimed more at the areas which do not have the same clear natural advantage.

Given the large reduction in communication costs there are new opportunities to use technology to reach new markets. Improved communication networks have reduced the importance of geography. The move away from manufacturing industries results in firms no longer having to locate close to raw materials or suppliers. The main reason behind a firm locating in a city location is to take advantage of the skilled labour force.

We saw from our results how reliant the areas of sustainable farming are on off-farm employment. Off-farm employment in these areas acts as an additional subsidy for farming. Some of these areas however are particularly vulnerable to shocks in the economy as any loss of employment means farming in these areas is no longer sustainable. It is therefore important to ensure these individuals are upskilled and trained in industries which are robust and contain steady employment opportunities. In order for rural areas to increase performance there must be an increase in the average skill level.

One of the biggest future challenges to rural policy will be in relation to farming areas in close proximity to major economic centres. There is a growing need to redefine what we mean by rural. Rural varies between areas that are close to urban areas which are more resilient compared to remote rural areas which are vulnerable to economic conditions. Rural policy 3.0 (OECD, 2016d) policy framework moves beyond farming and subsidising specific sectors towards making rural areas more competitive. This new approach also recognises the fact that there are different types of rural areas. It recognises the opportunities that exist in rural areas outside of agriculture. Rural areas with a higher quality of life but lower wages can attract and hold onto workers and their families.

Local labour markets have a large influence on the viability of farming. Distance and access to these markets can decide whether a farm is sustainable or vulnerable. The immobile nature of farm assets restricts farmers' job mobility, limiting their opportunities. Job opportunities may be beyond a reasonable commuting distance. Some of these vulnerable areas are also classified by high unemployment and a below average skills base. This makes it difficult to attract well paid, high-skilled jobs. The challenge facing policy in these areas will be to educate and upskill future generations in these areas. Innovative approaches using technology to allow individuals to work from home enabling them to remain farming should be explored. Given the increasing cost of living in our cities, this can be a more attractive alternative.

Chapter 7. Quantifying the impact of space on the distribution of welfare using spatial attributes[18]

7.1 Abstract

Welfare is not homogenous across space. Location can influence welfare both positively and negatively. Very often monetary income or earnings is used as a proxy for welfare. However a number of factors worth considering are ignored such as spatial attributes of the area. This paper will introduce a novel methodology (parametric match) which allows us to add a spatial dimension to a life-satisfaction micro survey which is not well defined at a spatial scale. We will overcome this problem by adapting a spatial microsimulation model to include the results from a life-satisfaction survey. The result is a detailed dataset which includes data on socio-demographic, socio-economic and life-satisfaction at a detailed spatial scale. The paper examines the differences between the distribution of disposable income and the distribution of life-satisfaction which is a function of the amenities in an area. Our results show that monetary income is not a good predictor of overall welfare. When we include a measure of life satisfaction into our analysis the richest areas in terms of monetary income no longer have the highest levels of welfare which factors in spatial attributes

Keywords: Spatial distribution, welfare, spatial microsimulation, parametric match, disposable income, self-reported well-being

7.2 Introduction

This paper builds on previous studies by examining welfare at a detailed spatial scale. Before measuring welfare, it is important to consider how welfare is defined. Individual welfare can consist of a number of components both monetary and non-monetary (Barr, 1998). Individuals may derive utility from a number of sources which can include more than just income and wealth. The impact of these sources on welfare can be measured using self-reported happiness surveys.

Welfare is not homogenous across space therefore it will be influenced across place (Kilroy, 2009). There are structural differences between regions (Heshmati, 2004) such

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as local specific policies (Shankar and Shah, 2003), local labour markets (Caselli, 2005) and agglomeration effects (Rosenthal and Strange, 2001). There exists a spatial dimension in welfare which can impact positively or negatively.

Some measures of welfare use monetary income as a proxy (Rey and Montouri, 1999). Previous studies have shown that welfare can vary across space (Sommeiller, 2006), there are not just differences in welfare between regions but also within regions, between people (Shorrocks and Wan, 2005). Different locations can have different levels of income (Sommeiller, 2006). However location affects more than just monetary income (Moro et al., 2008).

An individual's welfare will depend not only on their income but also on other non-monetary characteristics (Blanchflower and Oswald, 2004). Individual characteristics such as employment status and age will influence welfare. In addition to individual characteristics there are spatial attributes which also have an impact on welfare; spatial non-monetary characteristics such as; neighbourhood effects (Jencks and Mayer, 1990), urbanisation effects (Kuznets, 1955), and environmental characteristics (Roback, 1982) will have to be considered in a comprehensive measure of welfare.

Previous studies which have examined happiness in a spatial context have been restricted due to a lack of data and are typically at an aggregated spatial scale (Rehdanz and Maddison, 2005, Welsch, 2006, Stanca, 2010). Some studies have however attempted to observe between and within area welfare. Ballas and Tranmer (2011) used a multi-level model approach to simultaneously examine the variation in welfare at the individual, household and division level. However similar to other studies, data limitation meant they were limited to a spatially aggregated scale[19]. Brereton et al. (2008) used a spatially referenced life-satisfaction survey to examine the impact of spatial variables, including proximity on well-being at a small area level[20].

This study builds on previous research by examining how spatial attributes effect the spatial distribution of welfare and how this spatial distribution compares to the spatial distribution when disposable income is used as a proxy for welfare (O'Donoghue et al., 2013b, Kilgarriff et al., 2016). Using a parametric match (Decoster et al., 2007) the regression coefficients taken from Brereton et al. (2008) are used to estimate a spatial

19 UK District level of which there are 326, ranging in population from 25,000 to 1.1 million
20 Electoral District level of which there are 3,440, ranging in population from 66 to 38,894

distribution of welfare using life-satisfaction as a proxy for welfare. This study differs from Brereton et al. (2008) in that we are concerned not with the effect of the individual spatial components on welfare, but with the socio-economic and demographic characteristics of the areas.

7.3 Theoretical Framework

An individual's welfare was often thought to equal an individual's maximum utility. Typically utility is measured through income derived from goods, services and capital (Barr, 1998). It is assumed that utility can be directly measured by observing individuals revealed preferences in the market place. These decisions are made by rational individuals with full information who seek to maximise their utility (Dolan et al., 2008). Increasing number of studies however are discovering that people make inconsistent choices, are often not rational and are constantly comparing themselves to others. Self-reported measures of welfare offer an alternative method of measuring utility (Kahneman and Krueger, 2006). Economics have turned to self-reported measures of utility more associated with psychology (Dolan et al., 2008).

Traditionally welfare is represented as being equal to income:

$$w = y$$

However we know that more than just monetary income can affect welfare. Therefore:

$$w \neq y, \quad w = f(y)$$

Although we would expect monetary income and welfare to be correlated, they are not the same. By examining the spatial distribution of welfare and including the results of the happiness survey we are allowing for these non-monetary characteristics.

$W_{it} = \alpha + \beta X_{it} + \varepsilon_{it}$ (Graham, 2005)

Where W is self-reported welfare of individual i at time t, X is a vector of known variables (e.g. socio-economic and demographic) and ε the unobserved characteristics and measurement errors.

When we introduce space into our model of welfare, the equation becomes:

$W_{itk} = \alpha + \beta X_{itk} + \gamma A_{itk} + \varepsilon_{itk}$ (Brereton et al., 2008)

Where W represents the welfare of individual i, in time t, in location k, X is a vector of socio-economic and demographic variables and finally A is a vector of spatial attributes and variables. By introducing A we have extracted out some of the unobserved variability in welfare that is explained by location.

Drivers of Welfare

In this section we will conceptualise the drivers of welfare. The drivers of welfare that are influencing welfare between areas and the drivers that influence within areas between people are considered. How these differences, act as drivers of welfare is conceptualised. To motivate our theoretical discussion the concept of decomposing inequality into within and between spatial locations is considered. Discussions on what factors influence welfare between areas and what influences within areas. Within areas are place specific, personal characteristics and how they interact with place. From non-monetary perspective how peoples preferences are affected by characteristics. Drivers between areas are more structural. In table 7-1 the various drivers are grouped depending on how they influence welfare and what group of instruments they belong to.

Table 7-1: Between and within drivers of welfare

Group	Within	Between
Policy	Tax-benefit system EU and regional transfers	Tax-benefit system Labour markets EU and regional transfers Agglomeration economies Urbanisation effects Globalisation effects
Personal	Demographics Age distribution Employment status Monetary income	Property prices Access to 3rd level Monetary income Crime Local labour markets Neighbourhood effects
Environmental	Transportation Links Amenities	Transportation Links Climate Natural landscape Provision of services Externalities

Unemployment can often lead to greater levels of dissatisfaction. Effects of unemployment on satisfaction levels can however depend on the underlying economic conditions. In periods of high unemployment an individual is likely to feel less dissatisfied with themselves compared to periods of low unemployment. Also unemployment within their area is also important factors (Cohn, 1978). Those who are unemployed are twice as distressed as those who are employed (Oswald, 1997). Those who are unemployed are more likely to suffer from depression and are found to have lower happiness levels than those in low paid employment (Theodossiou, 1998, Korpi, 1997).

Happiness has been found be “u-shaped” with age (Blanchflower and Oswald, 2008, Clark et al., 1996). Space can impact on happiness via reference groups, people tend to be happier living in or close to rich neighbourhoods compared to poor ones (Firebaugh and Schroeder, 2009).

The relationship between happiness and money is a complex one. While money/income is seen to be a poor proxy for welfare, it can still have an impact on our level of happiness (Easterlin, 1974). A high level of income does not necessarily translate into high levels of welfare (Easterlin, 1995). The happiness we derive from income is a function of the income and wealth of those who live around us. Over a long period of time happiness is found not to increase, even though income has (Easterlin, 1974). There is a level of income above which our derived happiness from income begins to decrease. Nobody wants to be poor but once you reach a particular threshold an extra €1,000 is unlikely to make an enormous difference to your level of happiness as people tend to compare their situation with that of the norm (Oswald, 1997). Happiness thus varies directly with your own income and inversely with incomes of others (Duesenberry, 1949, Easterlin, 1974, Blanchflower and Oswald, 2004). It will depend on social comparisons (Layard, 2011). Brickman and Campbell (1971) refer to what they call a “hedonic treadmill” where an individual’s happiness remains stagnant despite efforts to advance or improve it. When an individual’s circumstances improve they tend to raise their expectations. A similar improvement in circumstances will not have the same effect on their happiness levels as their standards have been raised.

In addition to socio-economic and demographic drivers of happiness, happiness also varies across space (Glaeser et al., 2016). Individuals may derive welfare from local amenities, such as a scenic landscape (MacKerron and Mourato, 2013), facilities or the crime rate (Roback, 1982). Commuting (Stutzer and Frey, 2008) and other negative externalities such as airport noise (Van Praag and Baarsma, 2005). There can also be positive impact from spatial attributes (Brereton et al., 2008). For a comprehensive literature review of the impact of determinants on welfare see (Dolan et al., 2008)

The Stiglitz, Sen and Fitoussi Commission (Stiglitz et al., 2009a) suggested that statistical offices should start collecting data on subjective well-being by including questions into their surveys which evaluate people's life evaluations, satisfactions and goals. An example of this is the citizen driven "Canadian Index of Wellbeing" (CIW). The CIW framework (Michalos et al., 2011) consists of eight domains; community vitality, democratic engagement, education, environment, healthy populations, leisure and culture, living standards and time use. This measure of well-being is then compared with monetary measures such as GDP (CIW, 2012). There are limitations to measures of GDP being used as measures of overall welfare and the "success" of an economy (Kelpie, 2016). Traffic jams contribute to GDP through the usage of fuel however traffic jams have a negative impact on a person's well-being (Stiglitz et al., 2009a).

When using a different measure of welfare (both monetary and non-monetary) the rank and gap between regions may change. In this paper we will create two spatial distributions of welfare. The first distribution will use disposable income as a proxy for welfare. The second distribution of welfare includes the results of a happiness survey to include the impact of spatial attributes. The spatial distribution of disposable represents when just monetary income is used to measure welfare. The new distribution of welfare using life-satisfaction, takes into account spatial attributes and other drivers of welfare not directly measured using traditional revealed preference methods. This will therefore highlight how the two spatial distributions differ.

7.4 Methodology

Our methodology requires us to calculate the spatial distribution of the components of the drivers of welfare, and an estimate of how welfare relates to these drivers. Our dataset must contain income, demographic, environmental and climate data at a detailed spatial scale. Such a dataset is not available and will have to be created.

GIS and other online sources are used to collate the required environmental and climate data. Our environmental variables include the co-ordinates of transport infrastructure and other amenities. Similar to most countries and in particular this case study being examined, there is no detailed spatial income data. In overcoming this problem we draw our distribution of income from a spatial microsimulation model called SMILE (Simulation Model of the Irish Local Economy). Similar to income data, we do not typically know what people's welfare is. It is not published in census data. In the same way as income we have to use survey data. Statistical matching techniques are then used to match the results of a life-satisfaction survey and relating these results to the dataset created in SMILE.

Distribution of Income

To generate a spatial distribution of income we require income data at a spatial scale. Typically census data has poor or no income data but good spatial information, whereas survey data will typically have good income data but poor spatial information. The SMILE model, which is a spatial microsimulation model, helps overcome the problems associated with lack of income data at a spatial scale by linking the survey data with the census data (O'Donoghue et al., 2013a). The main objective of SMILE is to create a spatially disaggregated population micro-dataset by matching a number of variables that are common to both the census and survey datasets (Morrissey et al., 2008).

Spatial microsimulation is a method of generating a large synthetic micro-dataset at various geographical scales (Vega et al., 2016). SMILE is a static microsimulation model (Morrissey et al., 2013) which has been developed by the Rural Economic Development Programme, Teagasc and the School of Geography at the University of Leeds (Morrissey et al., 2008). It uses quota sampling (QS), which is a probabilistic reweighting methodology (Farrell et al., 2012b). Quota sampling works by first randomly ordering the micro data, it then samples from that micro data until the quotas, which are determined by the constraint variables, are filled (O'Donoghue et al., 2013a, Farrell et al., 2013a, Farrell et al., 2015). To ensure the household income data generated is representative, the output from the SMILE model is calibrated which is an alignment technique. Once calibration has been performed we have a dataset which contains market income as well as employment details at the division level for each individual in the population.

This paper will use the spatial distribution of income generated by SMILE. This micro-dataset created by SMILE contains socio-economic, demographic, labour force and income information at the individual and household level which is also spatially referenced. For an in-depth discussion on the SMILE model see (Morrissey and

O'Donoghue, 2013). Typically income is adjusted to take account of the varying composition of households. Equivalence scales are often used to overcome this issue. Income is measured at an equivalence scale to take account of the need of the household. For this thesis the National Scale is used (also known as ESRI equivalent scale A). This scale was chosen as it is the equivalence scale most widely used in Ireland (CSO, 2013, Nolan et al., 2002) and gives consistency across difference sources (Callan et al., 1996a). For this scale an adult is defined as being over the age of fourteen. The first adult is assigned a value of 1, each subsequent adult 0.66 and each child 0.33.

Subjective Well-being

Using subjective well-being (SWB) scores is one method used which takes account of the non-monetary aspects of an individual's well-being. SWB surveys attempt to measure an individual's life-satisfaction by asking them directly to state their life-satisfaction in a self-reported fashion. This is an example of a SWB question used in Brereton et al. (2008) where the following question was asked of respondents; "Thinking about the good and bad things in your life, which of these answers best describes your life as a whole? Respondents could choose a category on a scale of one to seven (As bad as can be; very bad; bad; alright; good; very good; as good as can be). The scale was developed by Likert (1932). One of the problems with standard economic theory is that it is based on revealed preferences, i.e. what we observe in the market place. Layard (2011) argues that if we are unable to tell how people feel, then how are we supposed to make them happy? This is where the usefulness of subjective well-being comes into play. Subjective well-being enables us to acquire human well-being directly (Frey and Stutzer, 2002). A subjective well-being approach allows the respondent to decide for themselves whether or not they have a good quality of life. It allows them to make this decision for themselves. No two individual's will be the same, what one person may view as a good standard of living, another may see as poverty and deprivation. This is the point in that it is subjective. It is an individual's evaluation of their own life.

Environmental Characteristics

Data on environmental characteristics such as crime, voting, climate, journey times and amenities in an area will have to be collated. Obtaining such data at a spatial scale can prove difficult as typically this data is at various geographical scales. The co-ordinates data for amenities such as rail stations was recorded using GIS. The distance between the centroid[21] co-ordinate and nearest amenity co-ordinate, for each of the proximity variables was obtained, with the distance to the nearest amenity, identified and recorded. This was carried out in STATA. Other variables such as the climate variables and distance to coast proved more cumbersome and required the use of GIS.[22] Upon competition of this task all of the required environmental and climate data at a detailed spatial scale is now available. We can now perform the statistical match.

Table 7-2: Environmental and climate variables included in the analysis

Environmental Variables:	Proximity to variables:
Precipitation	Landfill
Wind Speed	Hazardous waste facility
January minimum temperature	Coast
July maximum temperature	Beach
Average annual sunshine	Rail station
Average commuting time	Airport
Population density	Major road
Congestion	Sea port
Homicide rate	
Voter turnout	

Ordered Probit

Self-reported surveys of welfare and happiness are typically ordinal rather than cardinal. It is therefore best to interpret these results using ordered logit and probit equations. These regressions however normally return low R squared values, this is due to emotions and other components of "true" welfare driving the results, rather than variables we normally measures such as income and education (Graham, 2005).

Typically, in OLS we regress a continuous dependant variable Y on one or more independent variables X. As explanatory variables are added the residual variance decreases and the explained variance goes up by a corresponding amount. When our dependant variable is not continuous we can use binary and ordinal regression techniques such as a logit or a probit. These models allow us to determine the effect of

[21] The centroid point is the central most point in a district and will be equidistant to any point on the boundary line of the district

[22] Geographic Information System (GIS) – "a system for capturing, storing, checking, manipulating, analysing and displaying data which are spatially referenced to Earth" – Chorley, R. 1987. Handling Geographic Information. *Report of the Committee*.

the X's on the probability of being one category of the Y as opposed to another. One important characteristic of logistic regressions is that the errors are assumed to have a standard logistic distribution with a mean of 0 and variance of $\pi^2/3$. This has important implications as unlike in OLS where the variance of the dependant Y remains the same, in logistic regression analysis the explained and total variance will change as you add variables to the model. As a result unlike in OLS we are unable to compare coefficients across nested models as the dependant variable is scaled differently in each model (Williams, 2011).

The natural log of the odds ratio is the logit. The estimated probabilities from the logit model will always lie between 0 and 1. This probability also does not increase or decrease linearly, rather it approaches both zero and one at a decreasing rate (Gujarati and Porter, 1999).

So what is the difference between a logit and a probit? In truth they are very similar however a logit tends to have slightly fatter tails. In other words, in a logit model there is a slightly greater chance of having a value further from the mean compared to a probit model. The reason for certain disciplines using logit and others using probit seems to be as a result of history and tradition as both are useful. There is generally not much reason to choose one over another.

Distribution of Welfare

To create a spatial distribution of welfare, we require welfare data at a detailed spatial scale. Statistical offices however normally do not collect happiness or life-satisfaction information.[23] The results of a happiness survey will have to be utilised. Such a survey however while having rich data on welfare, has poor spatial data. A statistical matching technique will be utilised to match the life-satisfaction survey data to the SMILE dataset which has a rich spatial component. The statistical matching technique employed in this paper will be the parametric match.

The welfare coefficients (Brereton et al., 2008) will be applied. The parametric match begins by estimating a regression for one dataset, the coefficients generated from this regression are then imputed onto our other dataset using overlapping variables (Taylor

[23] The citizen driven "Canadian Index of Wellbeing" (CIW) collects such data. The CIW framework consists of eight domains within which there are eight indicators, the overall measure of wellbeing will comprise of 64 indicators. The percentage change in each domain is then calculated, from which the overall percentage change in wellbeing can be calculated. This is then compared with monetary measures such as GDP CIW 2012. How Are Canadians Really Doing? : Canadian Index of Wellbeing..

et al., 2001). In this case study we use the coefficients estimated in (Brereton et al., 2008) and impute these coefficients onto our SMILE dataset, using the overlapping variables. While our distribution may be normal in the donor dataset, that may not transfer across to the recipient dataset. For the parametric method you should aim to be using only a small number of variables with high significance. Including more may give rise to multicollinearity (Decoster et al., 2007).

We first take the utility function used in (Brereton et al., 2008):

$$U_{i,k} = \alpha + B' X_{i,k} + \gamma' A_{i,k} + \varepsilon_{i,k} \qquad i = 1....I, k = 1.....K$$

Where U represents utility of individual i in location k, X is a vector of socio-economic and demographic variables and finally A is a vector of spatial variables. Our variables from our SMILE dataset are then multiplied by the coefficients (betas) from table 7-3. This method is suitable as only one variable is being considered, welfare. Using the parametric method helps in overcoming the problem of a lack of life-satisfaction data. The main advantage of the parametric match is that, it is quicker to run when compared to the other statistical matching methods. Using the parametric method helps in overcoming the problem of a lack of. The parametric match provides a measure of welfare at the local level.

Welfare Measures

The two measures of welfare used are; disposable income and welfare. Welfare includes the results of the life-satisfaction survey, personal, climate and environmental variables. It measures an individual's life satisfaction. The two measures of welfare will be quintiles of mean equivalised household welfare at the Electoral Division (ED) level weighted by population[24]. The result is a coding 1-5 for the two measures for each of the 3,440 EDs[25].

Depending on the measure of welfare used we would expect to see some movement in the ranking of EDs. By cross tabulating the quartile variables for disposable income, welfare 1 and welfare 2, the amount of movement off the diagonal can be quantified. Four dummy variables are created for this purpose[26]. We cross-tab disposable income

[24] Each quartile will include 25% of the population
[25] Scale 1-4, poorest (1) to richest (4)
[26] Comparing the disposable income distribution to the welfare 1 distribution, we created a dummy interested in districts that moved up a quartile, we use a 1 when a district moves up, 0 when it stays the

with welfare. One dummy will focus on EDs that have moved up quintiles and another will focus on those that went down a quintile. If an ED moves up/down a quintile is it assigned a 1, 0 if it stays the same and missing if it has decreased/increased quartiles. A logit regression is performed to find what attributes are associated with an increase or decrease in the quintile of an ED. Finally we observe the Local Authorities which had the largest movement and whether these areas could be classified as urban or rural.

7.5 Data

In order to test the hypothesis that we defined in the theoretical section, applying the methodology that we outlined in the methodology section we require a spatially rich database that contains income, socio-demographic, life-satisfaction and environmental attributes information. The micro-dataset created by SMILE contains socio-economic, demographic, labour force and income information at the individual and household level which is also spatially referenced (Vega et al., 2016). The SMILE uses SAPS (2006), EU-SILC (2005) and POWCAR (2006) datasets. The Small Area Population Statistics (SAPS) for 2006 is a dataset which has a rich set of census information disaggregated down to the Electoral Division (ED) level.[27] The SAPS contains useful data on the composition of households at a local level but does not contain any data on income, life-satisfaction, well-being or spatial characteristics of an area (O'Donoghue et al., 2013b). The EU Survey of Income and Living Conditions (EU-SILC) dataset contains rich micro-data at the individual and household level but at a very spatially aggregated level, the NUTS2 regional level which has just two subdivisions.[28] A microsimulation approach is being used to overcome the lack of a spatially disaggregated dataset. The main objective or aim of SMILE is to create a spatially disaggregated population micro-dataset by matching a number of variables that are common to both the SAPS and EU-SILC (Morrissey et al., 2008).

The data on life-satisfaction comes from (Brereton et al., 2008). They used the results of a life-satisfaction survey (UCD, 2001) with a sample of 1,505 that were aged over 18

same and it will be missing if moving down. When looking at those that moved down the 1 and 0 are reversed.

[27] For the 2006 SAPS the ED level was the most spatially disaggregated level Morrissey, K., Clarke, G., Ballas, D., Hynes, S. & O'Donoghue, C. 2008. Examining Access to Gp Services in Rural Ireland Using Microsimulation Analysis. *Area,* 40**,** 354-364.. The SAPS for the 2011 census now contains more detailed demographic data at a Small Area (SA) level, of which there are 18,488. It should be noted this new SA geography is more effective in disaggregating urban populations but at rural level, may in place replicate existing ED geography

[28] The SILC is a national longitudinal survey which started in 2003.

and living in Ireland (Brereton et al., 2008). This also conforms with another well-being survey at the time the European Social Survey in Ireland in which Ireland also performed well (Delaney, 2009). The survey used in this paper was also spatially referenced meaning that the information could be linked to the respondent's location. Using GIS (Geographic Information System) this data was matched spatially to a national map of Ireland. The well-being data was combined with the dataset of spatial amenities and local specific factors at the ED level so that the well-being acts as a function of the various attributes of the area (Brereton et al., 2008).

Table 7-3: Coefficients from the Breteton et al., (2008)

Variable	Coefficient	t-statistic
Precipitation	0.0005	1.28
Wind speed	-0.3815	2.36
January minimum temperature	0.8082	3.33
July maximum temperature	0.0806	3.85
Average commuting time	0.0057	0.48
Population density	0.0061	1.92
Congestion	-0.0001	1.17
Homicide rate	0.0570	0.97
Voter turnout	0.0160	1.84
Proximity to landfill:		
Contains	-0.5145	1.87
Within 3 km	0.4332	1.55
Between 3 – 5 km	0.2998	0.95
Between 5 – 10 km	-0.2359	1.40
Proximity to hazardous waste facility:		
Contains	-0.4190	0.71
Within 3 km	-0.1993	0.54
Between 3 – 5 km	-0.3983	1.01
Between 5 – 10 km	-0.2888	0.89
Proximity to Coast:		
Within 2 km	1.1299	4.25
Between 2 – 5 km	0.2761	1.34
Proximity to beach:		
Within 5 km	-0.2248	0.73
Between 5 – 10 km	-0.1910	0.62

Proximity to rail station:		
Within 2 km	-0.2868	1.28
Between 2 – 5 km	-0.3531	1.37
Between 5 – 10 km	-0.0391	0.14
Proximity to airport:		
Regional:		
Within 30 km	1.2726	2.63
Between 30 -60 km	0.0543	0.27
National:		
Within 30 km	0.1404	0.40
Between 30 -60 km	0.5408	1.55
International:		
Within 30 km	0.4294	1.56
Between 30 -60 km	0.5371	2.16
Proximity to major road:		
Contains	-0.6040	1.97
Within 5 km	-0.5816	1.79
Proximity to sea ports:		
Within 3 km	-0.5826	1.63
Between 3 – 5 km	0.0023	0.01
Between 5 – 10 km	0.2877	0.85

Pseudo R^2 0.16

Data is also required in relation to the spatial variables and will have to be collected as this data is not freely available. Online sources and GIS were used to collate such data.[29] GIS is a powerful tool in gathering spatial data. Once the spatial variables dataset has been created, our spatial variables are then merged into our SMILE dataset based on district. It will then be possible to perform the parametric match using the coefficients generated in (Brereton et al., 2008). These coefficients will be simulated onto our SMILE dataset and the outcome will be a measure of welfare at the district level.

[29] Sources such as Ordinance Survey Ireland and Environmental Protection Agency websites

Table 7-4: Various Geographical Scales

Geographical Area	Number of Divisions
Electoral Division (ED)	3,440
Electoral Constituency	43
Local Authority	34
Garda Division	28
County	26

To ensure the parametric match is successful we need to ensure that our dataset replicates the one used in Brereton et al. (2008). It must be ensured that the scales and the calculations are identical. We will therefore be using the same variables. Roback (1982) included crime rate, population density and climate variables such as number of cloudy days, to calculate the quality of life rankings for US cities using the effects of the amenities/disamenities on wage and rent prices. As would be expected crime and poor weather indicators were disamenities, while population density and clear weather indicators were amenities. Blomquist et al. (1988) also used climate and crime variables but also included proximity to coast, landfill and disposal sites variables when examining quality of life rankings both across and within urban areas. Proximity to landfill and disposal sites were found to be disamenities and coast an amenity. The surrounding landscape is an important consideration when choosing where to live (Howley and Donoghue, 2011). As previously mentioned noise pollution associated with transport infrastructure is often found to have a negative effect on house prices. The coefficients from Brereton et al. (2008) show transport to be both an amenity and disamenity depending on type of infrastructure and distance. An International airport being more a disamenity compared to a regional airport. Noise externalities appear to be main cause. Since the Brereton et al. (2008) study a number of regional airports have since closed[30], the large positive coefficient on this variable will have a big effect on the welfare of those districts.

Due to data limitations some variables were not collected at a district level. The voter turnout percentage was collected at the electoral constituency level, congestion[31] collected at the County level[32], homicide rate[33] at the Garda division level. Table 7-4

[30] Number of regional airports has reduced from four to two.
[31] Number of cars per county divided by total length of primary roads in Local Authority
[32] County Tipperary is divided into north and south. This is the only county which has vehicle registrations divided in this way

gives details of the various divisions. The districts within each of these larger geographical areas were assigned the corresponding values.

7.6 Results

The four maps produced in GIS show the changing landscape of welfare depending on the measure used. We map the quintiles of median equivalised household disposable income and quintiles of median equivalised household welfare[34].

[33] Number of homicides per 100,000 of the population at the Garda Division level. It should be noted that Garda Divisions do not overlay with districts perfectly. Where the majority of the district lies in a division it is assigned to that division.

[34] Welfare includes the results of the happiness survey in relation to demographic, economic, environmental and climate variables.

Figure 7-1: Quintiles of Median Equivalised Household Disposable Income

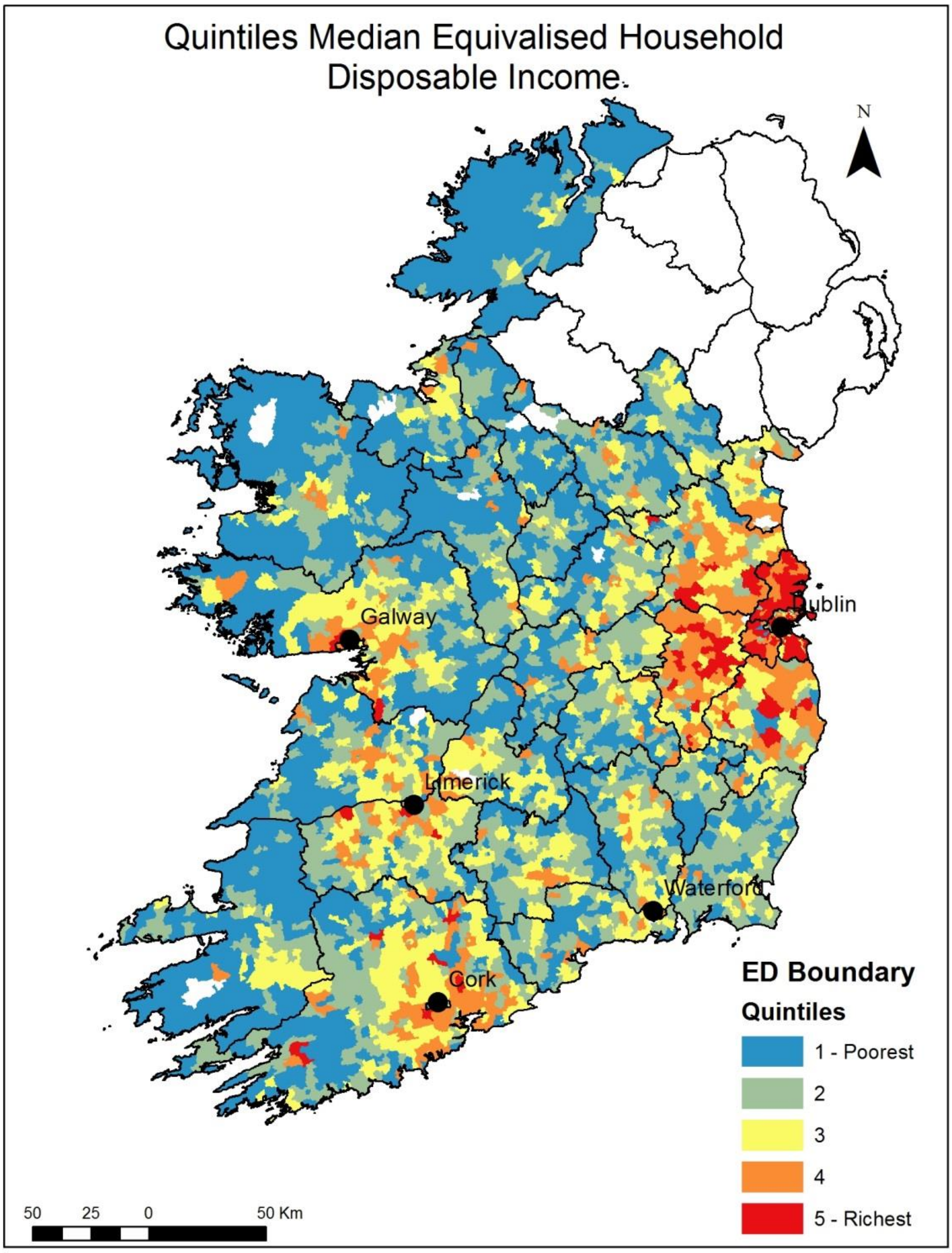


Figure 7-2: Quintiles of Median Equivalised Household Welfare

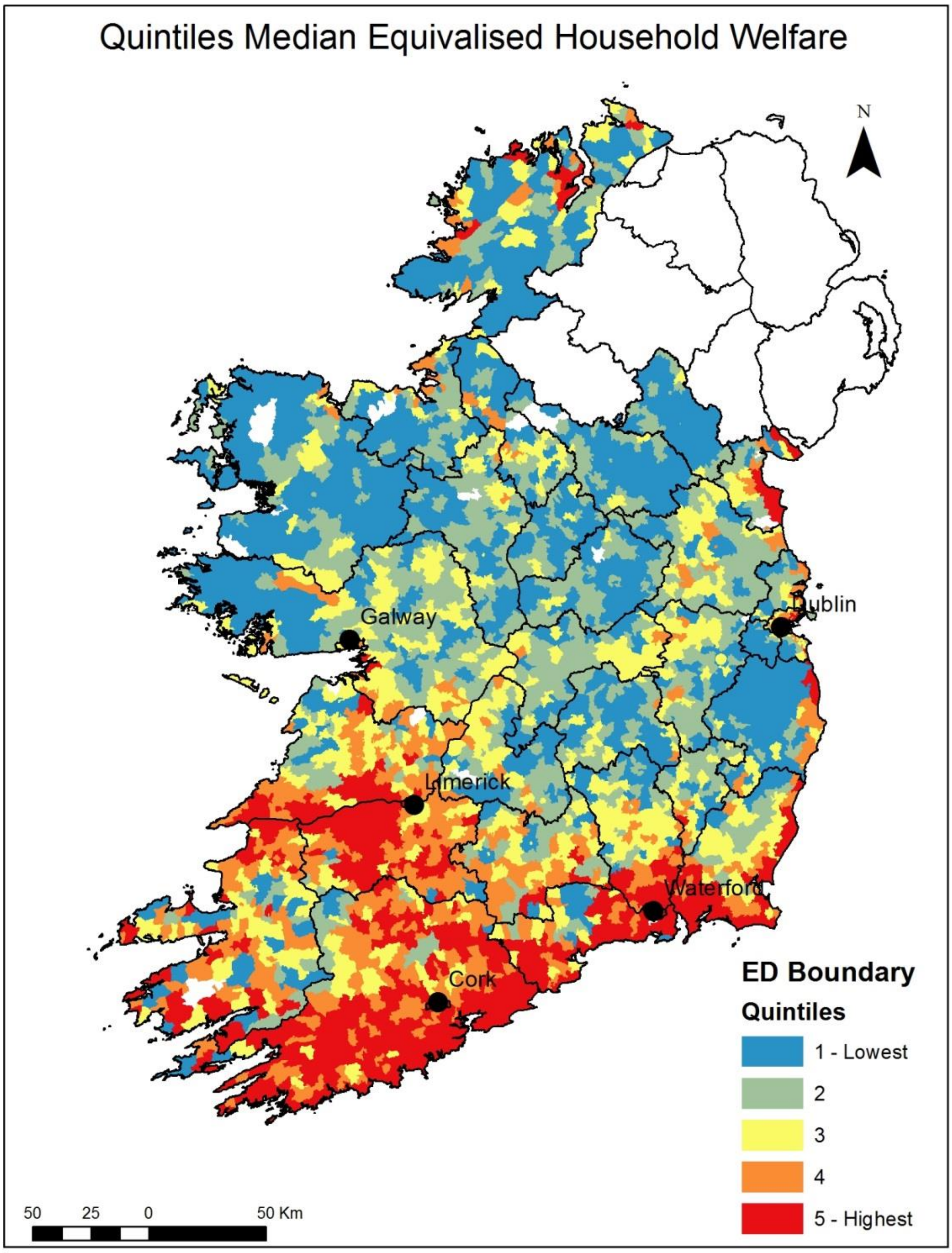


Figure 7-3: Quintiles of Median Equivalised Household Disposable Income (Cartogram)

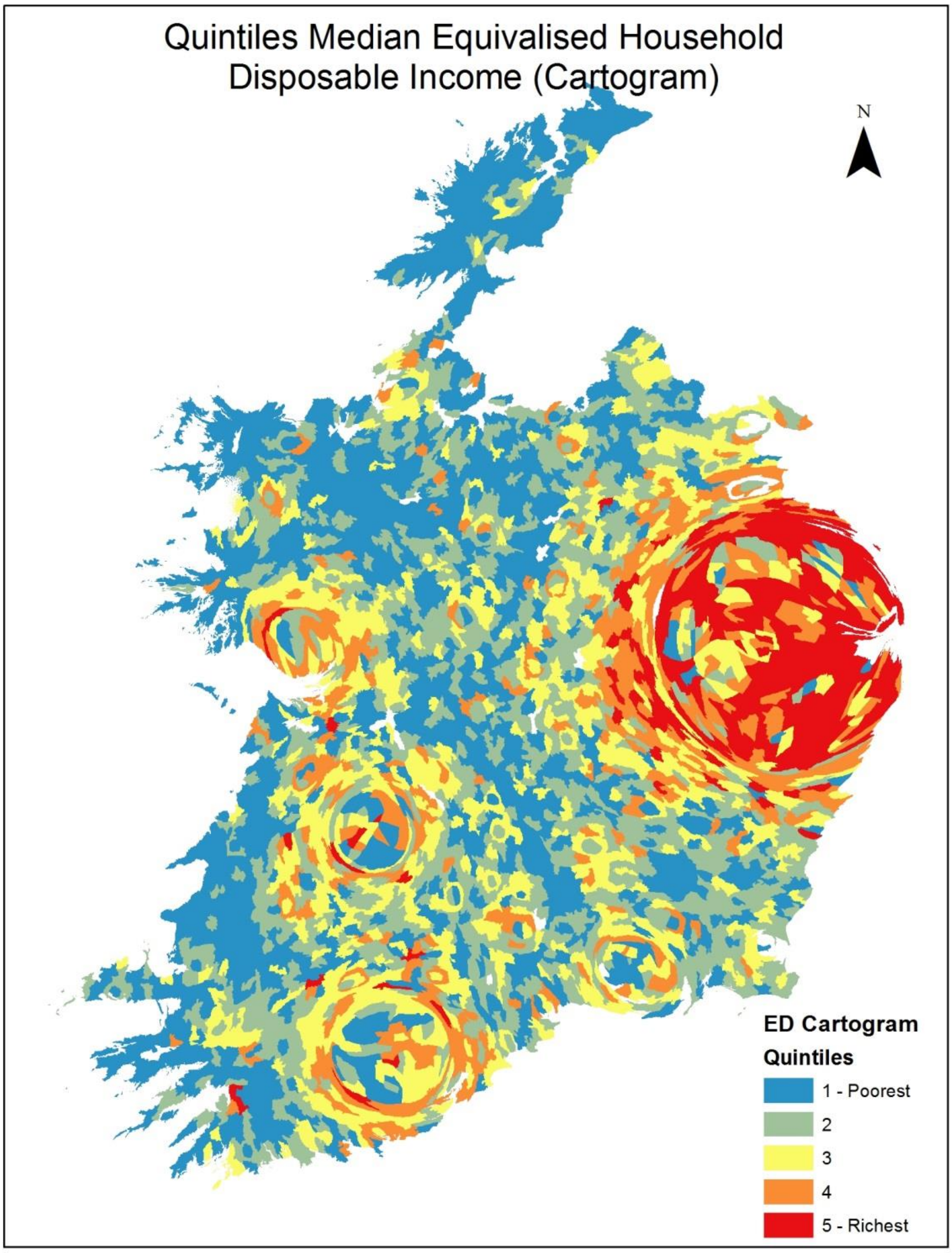
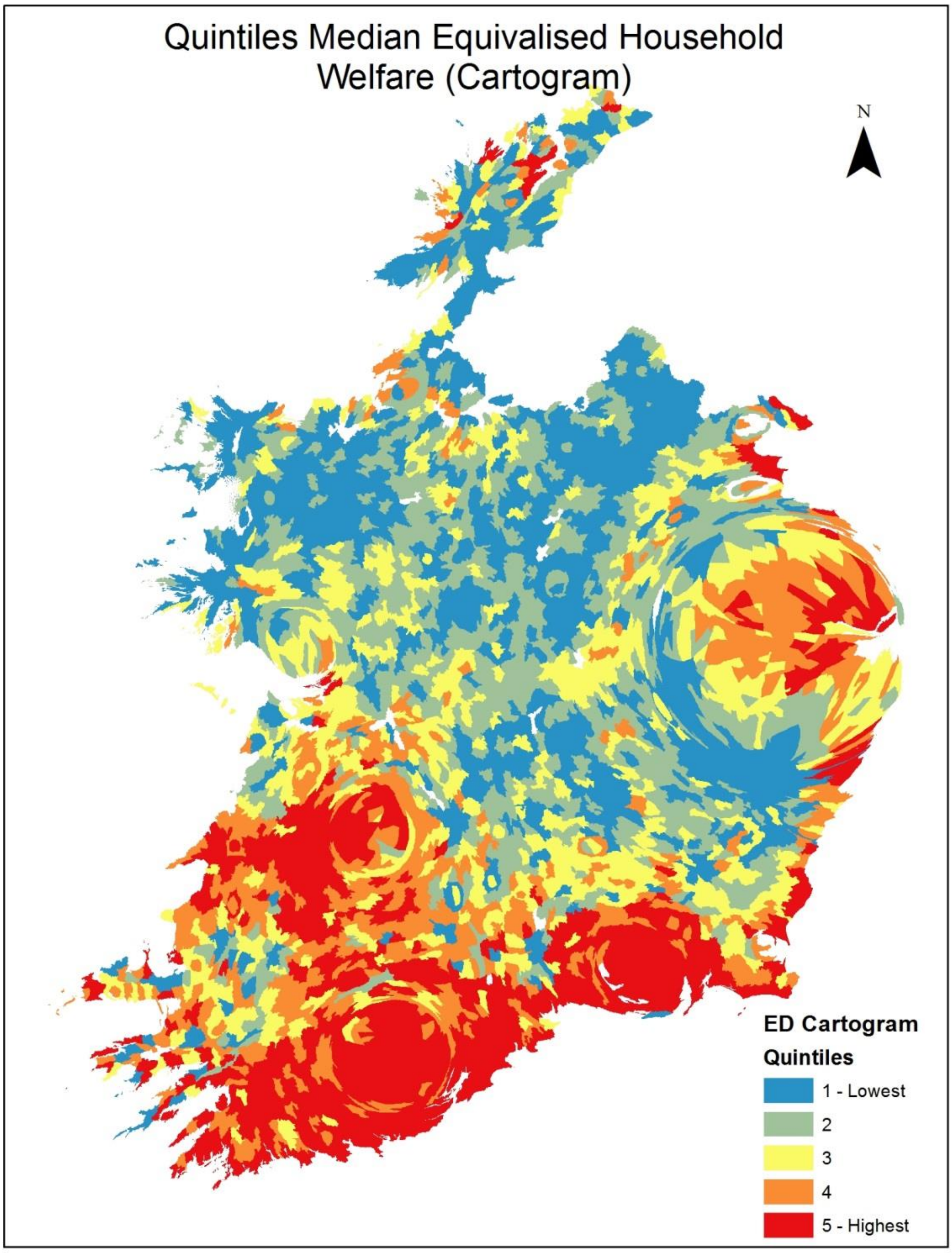


Figure 7-4: Quintiles of Median Equivalised Household Welfare (Cartogram)



Two of the maps presented are cartograms [Figure 7-3 & 7-4]. The area is re-scaled to reflect population (Tobler, 1973). As 28% of the population live in County Dublin which is only 1.3% of the total area rescaling will give a true picture of the distribution. The standard Electoral Division map of Ireland is adjusted to show the heavily populated areas more clearly. These cartograms were created in R using the "Getcartr" package which is based upon the Gaster and Newman Algorithm (Harris et al., 2017).

A quick observation of the two maps it is clear that there are differences. The distribution of welfare in each case changes depending on the definition of welfare being used. In Figure 7-1 we see a concentration of disposable income in the East (GDA and commuter belt). There is also a less pronounced area of high disposable income in the south-west and mid-west regions. What is consistent from all patterns observed is that the areas with the highest levels of disposable income are located largely in urban areas.

When including the environmental characteristics into the calculation of welfare our distribution changes. In Figure 7-2, the areas that have the highest levels of disposable income now have amongst some of the lowest levels of welfare. The levels of high welfare witnessed previously in the GDA are gone. The highest levels are located in the South-West region and also along coastal areas. Cork, Limerick and Waterford all experience high levels of welfare. Pockets of high welfare remain in Dublin however this is not as pronounced as before when only disposable income was considered. The north and midlands have amongst some of the lowest levels.

We will now use the Theil I_2 index, to investigate further the variability in welfare within these areas, examining between and within inequality.

Table 7-5: Theil I_2 Index of Inequality for each measure of welfare at ED level

Welfare Measure	Aggregate Inequality	Within-Group Inequality	Between-Group Inequality
Disposable Income	0.5331	0.5213 (98%)	0.0123 (2%)
Welfare	0.1644	0.0283 (17%)	0.1361 (83%)

The I_2 Index allows us to decompose variability into between-group and within-group. Similar to other findings (Jenkins 1995), the majority of the inequality in welfare is occurring within rather than between districts (Table 7-5). This however is not the case for welfare where 83% of the inequality can be examined inter-regionally. This can be explained by everyone within a district sharing the same environmental attribute values.

The two measures; disposable income and welfare; were divided into quintiles, with quintile five having the highest level of welfare. By looking at the cross tabulations between the two measures we can see how much movement there is when a different definition of welfare is considered. Each quintile contains approximately 20% of the population, because we are taking the populations of EDs the population percentage of each quintile will not sum exactly to 20%.

Table 7-6: Cross tabulation of Disposable Income and Welfare

				Welfare		
		1	2	3	4	5
	1	27.94%	21.72%	17.72%	14.93%	17.83%
	2	19.69%	22.49%	24.07%	14.36%	19.12%
Disposable Income	3	14.48%	19.33%	16.99%	21.77%	27.73%
	4	15.51%	22.87%	18.81%	18.73%	24.11%
	5	22.37%	13.58%	22.41%	30.20%	11.21%

From Table 7-6, we can see that the majority of population in quintile 5 (Q5) for disposable income, are now in quintile 3 (Q3) and quintile 4 (Q4) for welfare (~53% out of the 100%). The effect of this has seen some people move up a quartile between disposable income and welfare, e.g. Q1→Q2 (~21%), Q3→Q5 (~27%) and Q3→Q5 (~27%). Of those that were in Q5 for disposable income, only 11% remain in Q5 for the welfare measure.

Table 7-7 shows the population characteristics of the areas belonging to the various quintile groups. The results show that those in the highest quintile for welfare are not the areas with the highest levels of income. They are characterised by a lower employment rate, high unemployment rate, less densely population, lower education attainment, older, higher proportion of young people, lower house prices and a higher rate of deprivation. Despite all of this they have a reported higher levels of life satisfaction compared to the areas which have high levels of income, high house prices, lower unemployment rate, higher education attainment etc. This would suggest that some of these measures which are used to measure economic progress and therefore "better off" areas are not giving the entire story. The results from the life satisfaction survey show the importance individuals place on environmental characteristics and attributes such as living close to the coast or a beach.

Table 7-7: Summary Statistics of Q1 & Q5 for disposable income and welfare measures

	Disposable Income		Welfare	
	Q1	Q5	Q1	Q5
Employ. Rate	57.53%	64.33%	59.44%	59.03%
Unemp. Rate	13.57%	9.07%	12.79%	12.11%
Tertiary Education Rate	29.76%	45.41%	31.98%	35.48%
Pop. Density	309	3,421	168	1,192
Working Age Share	63.90%	70.56%	64.49%	65.86%
Old Age Dependency	24.46%	16.38%	21.18%	21.78%
Youth Dependency	32.61%	26.66%	34.39%	30.99%
Disposable Income (hh)	17,814	28,662	20,103	21,311
Average House Price	186,502	337,663	190,575	223,754
Average Population	686	4,355	1,113	1,448
Deprivation Rate	34.57%	16.16%	29.46%	26.77%

Table 7-8: Summary Statistics of the movers in welfare up and down quintiles

	Up 2	Down 2
Employ. Rate	58.21%	62.18%
Unemp. Rate	12.82%	10.77%
Tertiary Education Rate	32.53%	39.57%
Pop. Density	614	999
Working Age Share	64.50%	66.53%
Old Age Dependency	23.30%	16.71%
Youth Dependency	32.35%	34.17%
Disposable Income (hh)	19,424	25,495
Average House Price	204,636	258,318
Average Population	961	2,944
Deprivation Rate	30.44%	19.16%

7.7 Conclusion

The results from our analysis reinforce the findings of previous studies; monetary income is not a good predictor of overall welfare. When we include a measure of life satisfaction into our analysis the richest areas in terms of monetary income no longer have the highest levels of welfare which factors in spatial attributes. This is similar to Stanca (2010) where it was found that income had the lowest impact on life-satisfaction in Ireland.

We witnessed a shift from major urban areas to rural areas and areas where there was less urbanisation. The inclusion of the environmental attributes highlights the importance individuals place on location. The spatial distribution of welfare depends upon the definition of welfare we use. If disposable income is used as a proxy for welfare, those areas with the highest earners fare well. If however we consider other non-monetary characteristics such as climate and environmental variables the spatial distribution changes dramatically. This highlights the sensitivity of the spatial distribution to the definition of welfare.

The cities of Cork, Limerick and Waterford report high levels of welfare, suggest that quality of life is higher compared to Dublin. Living in the GDA has experienced the biggest change in welfare, levels of disposable income are higher than average, however unlike Dublin City, it does not have the same level of services and spatial attributes and therefore its rank falls. The high levels of income in the GDA are not compensating individuals enough for other aspects that are lacking such as the spatial attributes. Similar to Easterlin (1974) these findings suggest that income is an important determinant of welfare to a point, beyond which the spatial attributes become more influential.

The results show that living in an urban environment is not a strong determinant of having a high level of life satisfaction. Levels of welfare are highest in Cork, Waterford and Limerick and relatively high in Dublin City, however levels of welfare in Galway remain low. Before taking into account the spatial attributes Galway already had low levels of welfare. This appears to reinforce the point that an income threshold may exist. Income must reach this threshold before spatial attributes will have a positive impact on welfare. The pressure and stress of education, employment and income demands can have a negative impact on mental health. Income related pressures are one possible explanation.

Our results emphasise the importance individuals place on environmental characteristics and attributes, measures which are often ignored with measuring the deprivation or socio demographic profile of areas. It should therefore be the realisation for policymakers that concentrating economic activity in urban areas may not be the best solution if the goal is to improve individual’s overall levels of life satisfaction. What is clear is that individuals are willing to forgo extra income to have increased life satisfaction, better spatial attributes and hence higher levels of welfare. Not all rural areas however report high levels of welfare. This suggests the issue is more complicated than simply living in a rural area with good spatial attributes. Access to labour markets and other benefits of economic concentration may be impacting on welfare. Rural areas in the commuter hinterland of Cork, Waterford and Limerick report high levels of welfare. Areas around Dublin however do not. These areas around Dublin however could be classified more as suburban and experience the negative externalities of high commuting costs (Vega et al., 2016).

In addition to aspects of welfare such as income and commuting which can be monetised, there are these additional amenities and environmental attributes which impact on an individual's welfare. We have shown how utilising the parametric has enabled us to examine the differences between life-satisfaction and income in a spatial context. In the same way areas vary by income (Kilgarriff et al., 2016), they will also have different local environmental characteristics. The decomposition of welfare shows that even when we consider spatial attributes much of the variation in welfare occurs within rather than between districts. This important finding may warrant further investigation. Additional spatially rich welfare data is required to examine the spatial drivers behind this within area variation.

Chapter 8. The indirect economic costs of flooding: Evidence from transport disruptions during Storm Desmond[35]

8.1 Abstract

Flooding already imposes substantial costs to the economy. Costs are expected to rise in future, both as a result of changing weather patterns due to climate change, but also because of changes in exposure to flood risk resulting from socio-economic trends such as economic growth and urbanisation. Our understanding of the total costs of extreme weather events on the economy remains incomplete – in particular, existing cost estimates tend to focus on direct damages, excluding potentially important indirect effects such as disruptions to transport and other essential services. This paper estimates the costs to commuters of travel disruptions caused by flooding during the winter storms, specifically Storm Desmond, of 2015/16 in Ireland. We simulate, for every commuter in Co. Galway, their commuting travel times under the status quo and during the period of the floods and estimate the additional costs imposed on commuters. We estimate the total aggregate cost of extra time commuting due to flooding in Co. Galway during this period at €3.8 million. We also find that those already facing large commuting costs are burdened with extra costs by the floods. In areas particularly badly affected, extra costs amounts to 39% of earnings (during the period of disruption), while those on lower incomes suffer proportionately greater losses. While Storm Desmond was considered a 1-in-100 year event, under climate change we can expect events like this to occur with substantially greater frequency in future. Understanding the full economic costs of these extreme events is an important first step in preparing for a future with increased weather risk. Measuring the costs (direct and indirect) associated with a disruption to the road network is also necessary to determine if future investment in the flood proofing of roads is beneficial.

JEL codes: Q54, R11, R41

Keywords: flooding, climate change, transport disruptions, micro-simulation

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8.2 Introduction

Beginning with Storm Desmond in early December and followed by storms Eva and Frank, the winter of 2015/16 represented the wettest winter on record for Ireland. Rainfall levels in some areas were up to 250% of normal levels with over half of all stations recording their wettest winter on record (Met Éireann, 2016). Extensive flooding around the country caused widespread damage – hundreds of homes and businesses were flooded, and thousands more were cut off by flood waters. Almost €1.8 million in humanitarian assistance was paid out to affected households; close to €1m to farmers; local authorities received special funding of €18m for clean-up costs; while damage to the road network was estimated at over €100m. Aside from damages, the flooding also caused substantial disruptions to everyday life (350,000 customers suffered disruptions to electricity supply, and 23,000 households were placed on boil water notices). The flooding also resulted in substantial travel disruptions; in particular as a result of flooding on the road network (National Directorate for Fire and Emergency Management, 2016).

In an Irish context climate change is expected to bring more extreme weather conditions and an increased likelihood of river and coastal flooding (Sweeney et al., 2008). While Storm Desmond was considered a 1-in-100 year event, a near-real time attribution analysis found that events such as Storm Desmond. are now a 1-in-72 year event (van Oldenborgh et al., 2015). To manage flood risk effectively more needs to be known about the economic costs of flooding and its impact on economic activities in the short, medium and long term. With further warming (NOAA, 2017), these risks will likely multiply (IPCC, 2012, IPCC, 2013).

When measuring the impacts of a weather event, economists tend to focus on the costs of direct damages (destruction of assets and damage to buildings and infrastructure). In contrast the value of indirect costs, for example costs borne by the general public due infrastructure damage are less frequently quantified (OECD, 2014c). Within a commuting context, the blocking or closure of access routes can add not only extra time and expense to the daily commute but also unwarranted stress and uncertainty around whether a commuter will be late for work or not (Thieken, 2016). Road closures may also lead to congestion on segments of road which otherwise would not experience congestion (non-recurrent congestion). The less control commuters have over aspects such as traffic congestion and time pressure, the more stressful commuting can be

(Lyons and Chatterjee, 2008). In some cases it may not be possible to attend work due to being completely cut off or caught in traffic congestion. Commuters may also experience being late for work which may have career consequences. There may be a case to be made for more flexible working arrangements to alleviate this stress (Lucas and Heady, 2002). Over time commuters can adapt to these new road conditions and save time (Zhu et al., 2010).

Weather can also impact on road safety with a 75% increase in traffic accidents due to precipitation (Koetse and Rietveld, 2009). The costs of network disruptions because of more frequent adverse weather conditions may be very large. It is important to measure the net benefits of adaptations under future climate change scenarios (Snelder and Calvert, 2016). A greater understanding of the true costs of weather events such as flooding is only achievable when the economic analysis is broadened to include indirect costs associated with trip elimination. As such, the UK's Climate Change Risk Assessment (CCRA, 2012) believe the transport network to be at significant risk of flooding.

Commuting in Ireland involves substantial costs, in the form of the monetary costs of travel (ticket prices or the cost of fuel and other running costs for car drivers), as well as the welfare cost of the lost time spent commuting (Vega et al., 2016). Examining the welfare costs of commuting in Ireland, previous research estimated the combined commuting costs as equivalent to about 30% of daily wages for the average commuter in the commuter belt around Dublin, about 26% for the average commuter in Co. Galway and 20% in Co. Cork (see Vega et al., 2016). These costs reflect in part the heavy reliance on private car as mode of transport (76% in the Greater Dublin Area, 95% elsewhere in the country), as well as recent patterns of spatial development such the increasing urban sprawl around Dublin into areas with poor public transport infrastructure. The very high levels of car dependence, especially outside of Dublin, also highlight our economy's vulnerability to disruptions to the road network.

In this paper we measure the indirect costs to commuters associated with flooding of the road network. Specifically, combining time-stamped road closure data collected by Galway County Council in the aftermath of Storm Desmond (December 2015) with the Open Street Map road network, CSO Place of Work, School or College - Census of Anonymised Records (POWSCAR) 2011 and the SMILE model (Simulated Model of the Irish Local Economy) (O'Donoghue et al., 2012), this paper simulates the impact of storm Desmond on commuters in County Galway. Our research focuses on travel disruption rather than damage to transport infrastructure. Measuring the costs (direct and indirect) associated with a disruption to the road network is necessary to determine if future investment in the flood proofing roads is beneficial.

Section 2 introduces the data and methods used. We outline the POWSCAR dataset and how this is linked to the road network data and subsequently the flooded road dataset. We describe the OD cost matrix process and what GIS techniques were employed.

8.3 Data and Methods

To estimate the costs of the disruption to commuting patterns, we first require a baseline estimate of journey times for every commuter in our study area under normal circumstances – i.e. in the absence of disruptions to the road network. The Place of Work School Census of Anonymised Records (POWSCAR) dataset is a spatially referenced dataset which contains information for the entire population of the Republic of Ireland on their daily commute, collected as part of the national Census. This dataset has already been used to analyse traffic emissions (Brady and O'Mahony, 2011) traffic simulation (Suzumura et al., 2015) and mode choice for school children (Kelly and Fu, 2014). The data is made available as part of the Small Area Population Statistics (SAPS) – Census data aggregated to the electoral division (ED) level. There are 3,440 EDs with a mean population of 1,345. Individuals in the POWSCAR data are coded to their place of residence as well as their place of work/school/college. The POWSCAR data contains information on the residential ED, work ED, distance to work, journey time and travel mode. However, distance to work and journey times are self-reported by individuals filling out the Census form, and are therefore liable to contain error. For this reason we use an Origin-Destination (OD) cost matrix approach to estimate journey times for each individual commuter in our study area. This process is then repeated accounting for the disruptions to the road network caused by flooding over a 17 working day period (9th December 2015 – 5th January 2016). Although information on the number of vehicles affected or additional journey time imposed is not available, detailed data on the exact segments of the road network that were flooded and for how long each road segment remained partially or entirely closed is available.

Table 8-1: POWSCAR Modal Share by Area

	Greater Dublin Area	Other Provincial Cities	Other Towns and Rural Areas
Definition	Dublin County Borough, Fingal, South Dublin, Dun Laoghaire-Rathdown, Kildare, Meath, Wicklow and Louth	Cork, Limerick, Galway and Waterford	Elsewhere
Modal share			
Car (%)	75	88	89
Public Transport (%)	25	12	11
Average commuting distance (km)	20.74	6.2	33.16
Number of Commuters[36]	875,706	111,790	1,136,079

Table 8-1 shows the POWSCAR modal share broken down by area. Our study area (County Galway) is heavily reliant on the car (88% modal share) with only 12% of commuters using public transport daily; this is even lower when we consider the rural areas of Galway outside of the city. Galway contains 234 electoral divisions.

[36] Does not include those who walk or cycle.

Table 8-2: Regional Summary Statistics

	Galway			
	City	County	GDA	National
Old Dependency	12.6%	19.4%	15.2%	17.4%
Youth Dependency	22.3%	35.0%	30.5%	31.9%
Employment Rate	56.4%	60.3%	61.0%	58.8%
Working Age Share	74.1%	64.8%	68.7%	67.0%
Unemployment Rate	11.8%	12.4%	11.9%	12.7%
No car households	23.7%	11.2%	20.7%	17.5%
Tertiary Education Share	40.9%	36.6%	38.8%	36.2%
At Risk Poverty	17.6%	17.5%	13.2%	16.0%
Pop. Density	1,489	29	247	65
Population	75,529	175,124	1,927,053	4,588,252
% of Pop	1.6%	3.8%	42.0%	100.0%

The area of study in this paper is Galway City & County. The administrative area used is the electoral division of which Galway contains 234. Table 8-2 shows a number of socio-economic and demographic indicators for the region. The city is characterised by having a highly educated, working age population, whereas the county has both a high rate of elderly and youth dependency compared to the national average. The unemployment rate for both city and county is below the national average although the at-risk of poverty is higher.

Table 8-3: Study Area Characteristics

	Galway								
	City	County	Town 5,000 - 9,999	Town 3,000 - 4,999	Town 1,500 - 2,999	Village 2,000	Rural	GDA	National
Old Dependency	12.6%	19.4%	20.6%	12.8%	18.8%	18.7%	21.3%	15.2%	17.4%
Youth Dependency	22.3%	35.0%	33.5%	36.5%	33.8%	35.7%	34.7%	30.5%	31.9%
Employment Rate	56.4%	60.3%	56.1%	67.8%	62.1%	61.8%	60.2%	61.0%	58.8%
Working Age Share	74.1%	64.8%	64.9%	67.0%	65.5%	64.8%	64.1%	68.7%	67.0%
Unemployment Rate	11.8%	12.4%	16.0%	10.1%	11.7%	12.0%	12.5%	11.9%	12.7%
No car households	23.7%	11.2%	18.7%	7.7%	12.7%	11.0%	9.4%	20.7%	17.5%
Tertiary Education Share	40.9%	36.6%	34.5%	48.0%	38.8%	38.1%	32.6%	38.8%	36.2%
At Risk Poverty	17.6%	17.5%						13.2%	16.0%
Pop. Density	1,489	29	99	102	40	38	18	247	65
Population	75,529	175,124	24,424	16,414	15,491	41,339	73,826	1,927,053	4,588,252
% of Pop	1.6%	3.8%						42.0%	100.0%

A further breakdown of the county by urban-rural classification [Table 8-3] shows that the majority are living in rural areas or close to small villages. There is a higher prevalence of car households in the county compared to the city. Despite the high rates of old age dependency in the county area, tertiary education share remains high. Employment rates in the county are also higher on average compared to the city. The younger population would suggest these are commuters.

Calculation of the Origin-Destination Cost Matrix

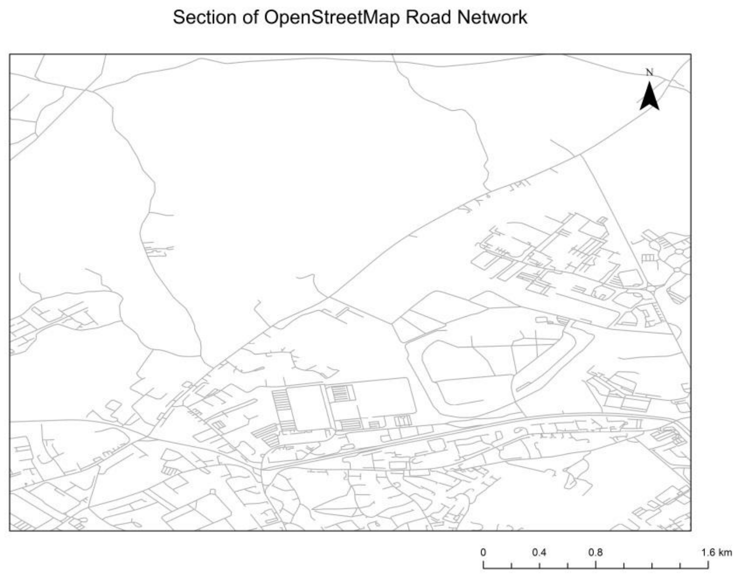
Regarding the sample selection for this paper, in terms of modes of transport our data concerns flooded roads so we do not include pedestrians, cyclists or train users in the analysis. Only individuals who are in employment and commute are included. Students, those who work from home or the unemployed are not included. This analysis is also restricted to commuters whose journeys start and end within County Galway. As data on the extent or precise locations of flooding on the road network outside of County Galway was unavailable, this paper cannot say whether commuters traveling outside the county had their journeys disrupted. It would be incorrect to assume that commuters travelled unimpeded once outside County Galway – for example, the town of Athlone which lies just outside the Galway county boundary was particularly badly affected by flooding during this same period (Pope, 2016). Again this data constraint would tend to cause us to underestimate the total cost of the disruption to travel caused by the flooding in County Galway. After removing individuals living or working outside of County Galway as well as the other specifications mentioned, the sample comprises 48,000 individuals.

Using the centroid of each electoral division (ED) in County Galway, an OD cost matrix was calculated for the 234 EDs that comprise in County Galway. The procedure used to estimate journey distances and times operates as follows: For the road network we use data from OpenStreetMap[37] (Haklay and Weber, 2008) which is an open source dataset. This road network dataset contains detailed information in the form of a shape file [Figure 8-1]. In order to calculate the time it takes to travel a segment of road, a speed and distance is required. The distance is measured in ESRI's ArcMap, while the speed values attributed to sections of the road network comes from the RSA (2013) free speed survey, which publishes average car speeds by road class[38].

[37] http://download.geofabrik.de/europe/ireland-and-northern-ireland.html

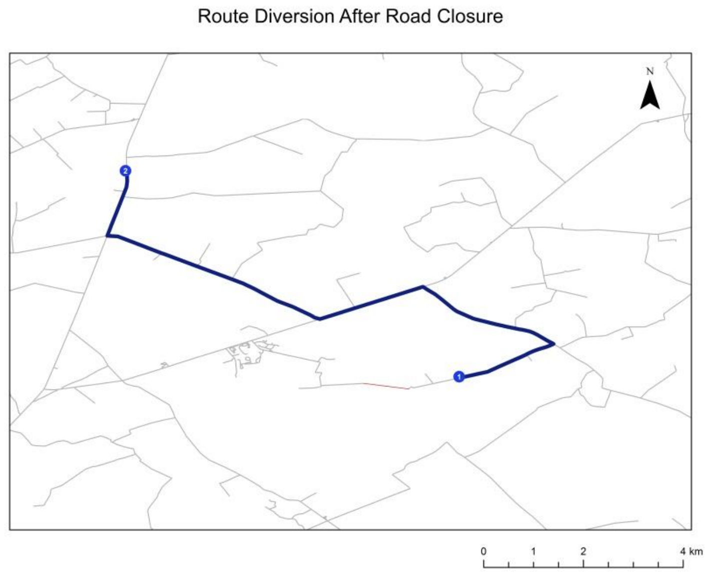
[38] Five road classes in the model; Motorway, National Primary, National Secondary, Regional and Local

Figure 8-1: Section of OpenStreetMap Road Network



The calculated OD cost matrix was combined with the POWSCAR data to estimate actual commuting patterns in our study area – i.e. average journey times and distances travelled to work for commuters living in each electoral division within our study area – see [Figure 8-2] for an illustration. This gives us a baseline estimate of commuting patterns in County Galway in the absence of any disruptions to the road network.

Figure 8-2: Section of Road Network showing flooded road and Origin-Destination points



Disruptions to the road network due to flooding

As noted above, Galway County Council collected detailed daily data on the effects of flooding on the road network within the County[39]. The data contains information on whether a road is open, closed, passable or only one-lane open. A unique identifier is given for each road segment and the data is time stamped, enabling us to observe precisely which segments of the road network were affected on a particular day at a particular time. The data covers a 17 working day period of disruption (9th December 2015 to 5th January 2016). In some cases the data were updated twice during the day (morning and afternoon). Figure 8-3 shows the length of roads flooded per ED.

This data was then linked to Galway Road Network data[40]. Unfortunately there was a data mismatch between the OpenStreetMap dataset (which contains more road segments) and the Galway Road Network data. Using the QGIS GRASS plugin, it was possible to highlight the road segments in the OpenStreetMap and data recorded on whether they were flooded and what dates the road was closed or partially flooded.

The OD-cost matrix procedure described above was then re-run accounting for the disruptions to the road network caused by the flooding. In practical terms, this involves removing road segments that were impassable, and reducing the average speed to 10 km/h where the road was partially flooded. The status of affected roads was updated 11 times by Galway County Council during the 17 working day period studied. We therefore re-run and re-calculate the OD model 11 separate times, each time with an updated configuration of available routes and speeds, in addition to running the status quo scenario described above where we assume no disruption to the road network. As before, the software attempts to calculate the fastest route from A to B, given the restrictions on the road network we impose due to observed flooding. This was carried out in ArcGIS using the network analyst tool.

An important limitation here is that, as noted earlier, we cannot observe actual traffic volumes on each route. Our procedure for simulating the impact of the floods on journey times therefore takes no account of the possible additional traffic volumes on non-flooded routes due to the displacement of traffic from affected routes. It is possible

[39] https://data.gov.ie/dataset/floodedroadsdec2015 - special thanks to Mark Conroy (Galway County Council) for helping us source the data

[40] https://data.gov.ie/dataset/galway-county-roads-networkc9c86

that in some cases such congestion effects on non-flooded routes may have been substantial (Kelly, 2015, Galway Bay FM Newsroom, 2015, Connacht Tribune, 2015). This limitation would tend to cause us to underestimate the impacts on journey times due to flooding.

The total additional journey time for each Origin-Destination combination is calculated for the entire period of disruption, and these values assigned to each commuter in the POWSCAR dataset, merging on place of origin and place of destination. It is important to note that this procedure assumes that every commuter travelled to work on each working day during the period of disruption. This simplification may cause us to underestimate absenteeism because of the disruption. In the aftermath of widespread flooding in central Europe in June 2013, businesses reported by as much as 60% of their workforce were affected either by being absent or late from work (Thieken, 2016). Given a lack of detailed spatial information we are unable to differentiate between the likelihood of a worker being late or absent. We make the assumption that all workers made an attempt and reached their work destination. After the calculation of the OD cost matrix we now have an estimate of the impact of the flooding disruption on the road network, in terms of the additional time spent commuting for each commuter in the study area during the period of disruption.

Figure 8-3: Length (m) of roads flooded in an ED

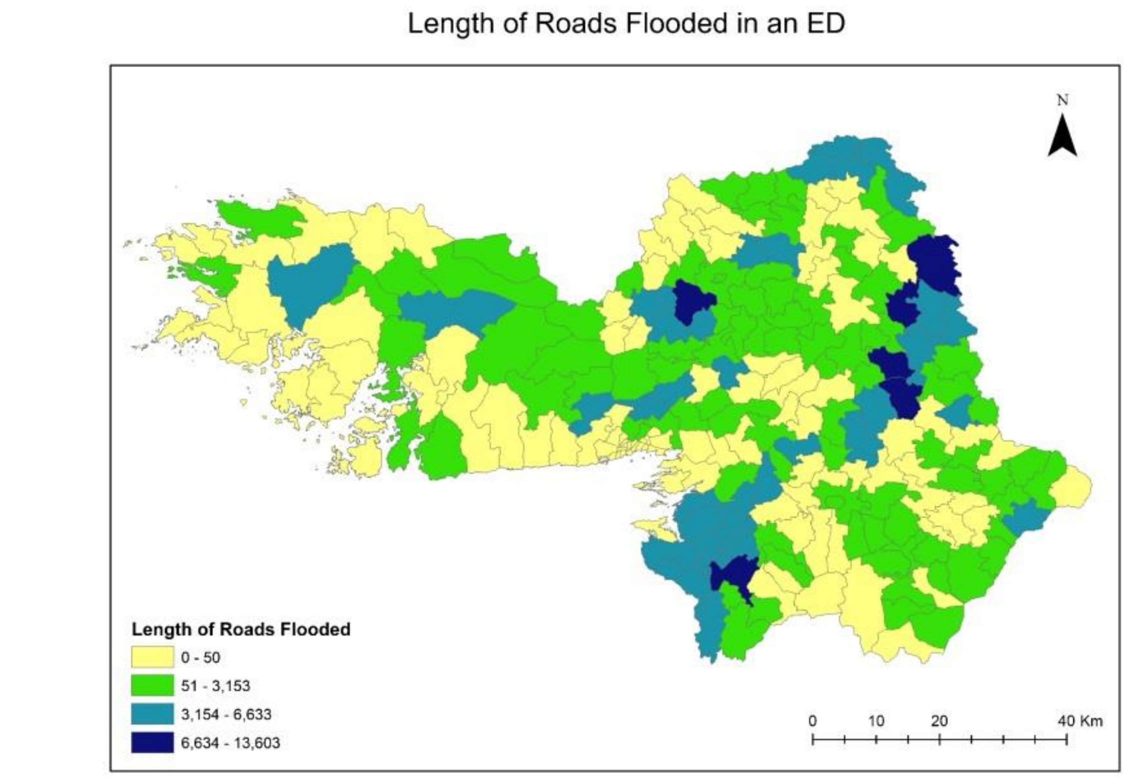


Table 8-4: Flooded Road Segments by Road Class

Road Class	Number of Segments
National Primary	9
National Secondary	29
Regional	52
Local Primary	102
Local Secondary	66
Local Tertiary	44
Unassigned	97

8.4 Subjective Value of Travel Time (SVTT)

Economic theory on the valuation of time was first introduced in the 1960s with Becker's (1965) seminal work on the allocation of time. Transport economists have long been interested in the value of time, which has become a key element in the overall identification of the costs of transport required as part of any cost-benefit transport appraisal framework.

Commuting trips are ubiquitous, yet their characteristics vary from person to person and place to place (Lovelace et al., 2014). Over the last decades, and following pioneering research by (Train and McFadden, 1978), the analysis of travel behaviour has been increasingly based on the use of discrete choice models. These models are used to describe the probability of a decision-maker choosing a particular option from a set of alternatives, as a function of the attributes of the alternatives and the demographic and socio-economic characteristics of the individual (Train, 2009). Similar to the original research by Becker (1965), discrete choice models are grounded in consumer utility theory whereby the individual chooses among alternatives with the aim of maximising personal utility. Based on this theoretical and empirical background, Vega et al. (2016) estimate the SVTT for three subsample of the Irish population using data from the 2011 Census of Population of Ireland (see Vega et al., 2016 for details). Table 8-5 shows the SVTT estimates, which are included in our model.

Table 8-5: VoT by Area

Area	Commuting VoT (Euro/h)
Greater Dublin Area	10.2
Dublin	8.96
Commuting Counties	14.1
Other Provincial Cities[41]	21.2
Other Towns and Rural Areas	6.07

Overall, the SVTT for commuting in the GDA is €10/hour. The largest SVTT is obtained for other provincial cities, while the SVTT for commuters in Other Towns and Rural Areas is substantially lower. A possible explanation for this result is that those areas included under other provincial cities are primarily comprised of urban and sub-urban districts, possibly subject to heavy traffic congestion due to limited public transport options and in some cases, longer commuting distance. Overall, the values obtained from the analysis are in line with those used by the Department of Transport Common Appraisal Framework (DTTAS, 2016).

Direct Travel Costs

In estimating the travel cost we use estimates of transport costs per km from the NTA (2011). This measure per km considers the standing costs (insurance, car licence and

[41] Other provincial cities include Galway, Cork, Waterford and Limerick.

depreciation) of owning a 1200cc – 1500 cc car, petrol costs and any wear and tear to the vehicle.

The public transport costs are calculating using the average cost for a single ticket including bus and rail. The costs are detailed in Table 8-6. These costs are broadly in line with the subsidence payments which public sector workers receive for "mileage" (Impact Trade Union, 2009) and also the AA's published annual cost of motoring (AA, 2016).

Table 8-6: Transport costs per km by mode

Transport Costs per km	€
Car Costs	
Urban Area	0.62
Work in Urban Area	0.63
Rest	0.58
Public Transport	
GDA	0.50
Galway	0.15
Cork	0.18
Waterford	0.14
Limerick	0.16
Rest	0.25

Source: NTA

When we combine the two cost functions we get equation 1, which is total cost of a one way commute for a commuter.

$$Cost = \left(Distance_c * TC_{mp}\right) + \left(Time_c * \frac{Vot_p}{60}\right)$$

Where distance is the distance from residence to work for commuter c, TC the transport cost per km for transport mode m in location p, Time the journey time from residence to work for commuter c, Vot the value of time in location p. This cost measure is then multiplied by 34 to get the total cost of commuting over the 17 day period.

8.5 Spatial Microsimulation

Aside from estimating the magnitude of the disruption to travel caused by flooding in terms of additional journey times and associated costs, we are also interested in understanding how this burden is distributed across the population of commuters. In order to get a better sense of the magnitude of this burden, we would like to compare the costs imposed by the flooding on commuters with the incomes of those affected. Similarly, we would like to understand how the additional costs imposed by flooding are distributed across socio-economic groups. In order to understand how the additional costs imposed by flooding are distributed across socio-economic groups, spatially referenced micro-data is required.

As noted above, POWSCAR data is the only population data source for Ireland with detailed individual commuting information. This data however contains no income information. In the contrast, the SILC is a nationally representative survey containing 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, which contains two regions, the Border, Midlands and West region and the South East region). As such, any analysis using the SILC survey is constrained to the national level. Furthermore, the SILC dataset does not contain commuting data. Using a matching algorithm to link the data in the SILC with the small area level SAPS and POWCAR data, a much richer dataset would be obtained that would allow an examination of the variations in the value of commuting travel times relative to disposable income across the Irish regions. One can use spatial microsimulation techniques to accomplish this.

The development and application of spatial microsimulation models offers considerable scope and potential to analyse the individual composition of an area so that specific policies may be directed to areas with the greatest need for that policy (Birkin and Clarke, 2012). The Simulated Model of the Irish Local Economy (SMILE) is a spatial microsimulation model. The first version of SMILE, referred to as SMILE2002 for the purpose of this paper, was based on 2002 Census of Population data and the Living in Ireland Survey (2001) and used a combinational optimisation algorithm, simulated annealing (Morrissey et al., 2008). However, although 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 the simulation (Farrell et al., 2013a, Hynes et al., 2009b). As a result, to create SMILE 2006 and match the Small Area Population Statistics (SAPS, 2006), SILC (2005) and POWCAR (2006) datasets a more computationally efficient method known as quota sampling was developed by Farrell et al., (2013). For a complete technical overview of the SMILE 2006 and the Quota Sampling methodology please see Farrell et al. (2013a).

SMILE creates synthetic data. As such, validation of the output created by SMILE is an integral component of the model's construction. Calibration through alignment (Morrissey and O'Donoghue, 2011, Morrissey et al., 2013) offers a method to ensure that the output produced by the SMILE model is consistent with real world data. A full description and application of the calibration method in terms of labour force and income distributions and socio-economic characteristics and health service utilisation is provided by Morrissey and O'Donoghue, (2011) and Morrissey et al., (2013), respectively. Calibration through alignment was used to ensure the income estimates produced for the purpose of this paper. Post calibration, we now have a population dataset which contains income and demographic data at the ED[42] level (Vega et al., 2016). On linking the POWSCAR dataset to the SMILE data we have a dataset which contains individual socio demographic and economic information as well as information on their commuting time, distance and mode. Linking this data to the OD cost matrix calculated above, we can measure the impact of the flooding disruption on the spatial distribution of employment income at the electoral division level.

[42] Since 2011 SAPS are available at a new, more spatially disaggregated unit, Small Areas (SA) of which there are 18,488. We however will only consider the ED level as there have been some issues around microsimulating at the SA level.

Table 8-7: Validation of Simulated Income by County

County	CSO €	SMILE €	Real Difference €	% Difference	CSO Rank	SMILE Rank
Dublin	28,834	29,297	464	1.61%	1	1
Limerick	26,743	26,094	-649	-2.42%	2	2
Kildare	25,346	25,100	-247	-0.97%	3	3
Wicklow	24,560	24,595	34	0.14%	5	4
Cork	24,621	23,973	-648	-2.63%	4	5
Meath	24,218	23,425	-793	-3.27%	6	6
Waterford	22,922	23,410	488	2.13%	7	7
Louth	22,698	23,371	673	2.96%	9	8
Clare	22,266	22,840	573	2.57%	13	9
Tipperary North	22,490	22,838	349	1.55%	10	10
Tipperary South	22,483	22,534	51	0.23%	11	11
Westmeath	21,868	22,331	463	2.12%	15	12
Galway	22,755	22,218	-537	-2.36%	8	13
Carlow	22,345	22,081	-265	-1.18%	12	14
Sligo	22,002	22,004	2	0.01%	14	15
Kilkenny	21,711	21,512	-199	-0.92%	17	16
Mayo	21,127	21,350	223	1.06%	20	17
Monaghan	20,482	21,282	800	3.91%	23	18
Kerry	20,929	21,243	314	1.50%	21	19
Leitrim	21,833	21,107	-725	-3.32%	16	20
Longford	20,471	21,039	568	2.78%	24	21
Wexford	21,255	20,969	-286	-1.35%	19	22
Offaly	20,071	20,922	851	4.24%	26	23
Laois	21,545	20,878	-667	-3.09%	18	24
Cavan	20,621	20,597	-24	-0.12%	22	25
Roscommon	20,413	20,563	150	0.74%	25	26
Donegal	19,097	19,224	127	0.67%	27	27

8.6 Results

Our results are split in two. The first part of the analysis focuses on the impacts of the flooding across space. The second part examines the distributional and individual impacts. This ensures there is an inter/intra analysis of flooding on commuting.

Spatial impacts of flooding on commuting costs

Observing the commuting pattern before the flooding event, it is evident that those on the outer Galway city commuting belt already have high commuting costs [Figure 8-4]. Some of these areas also overlap with the areas worst affected by the floods [Figure 8-3]. Direct commuting costs for the worst affected areas ranged from €278 - €680 per commuter over the 17 day period. In terms of commuting times, for some commuters the flooding involved an extra 30-60 minutes per day travel time [Figure 8-5].

Figure 8-4: Average costs per commuter - normal scenario

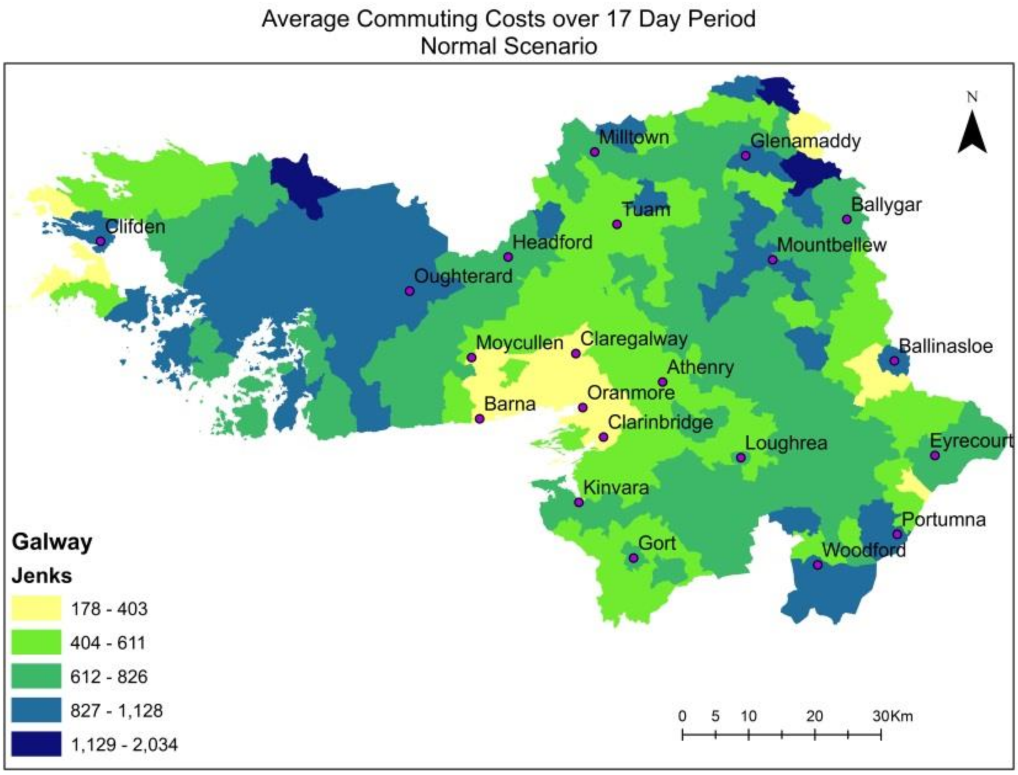
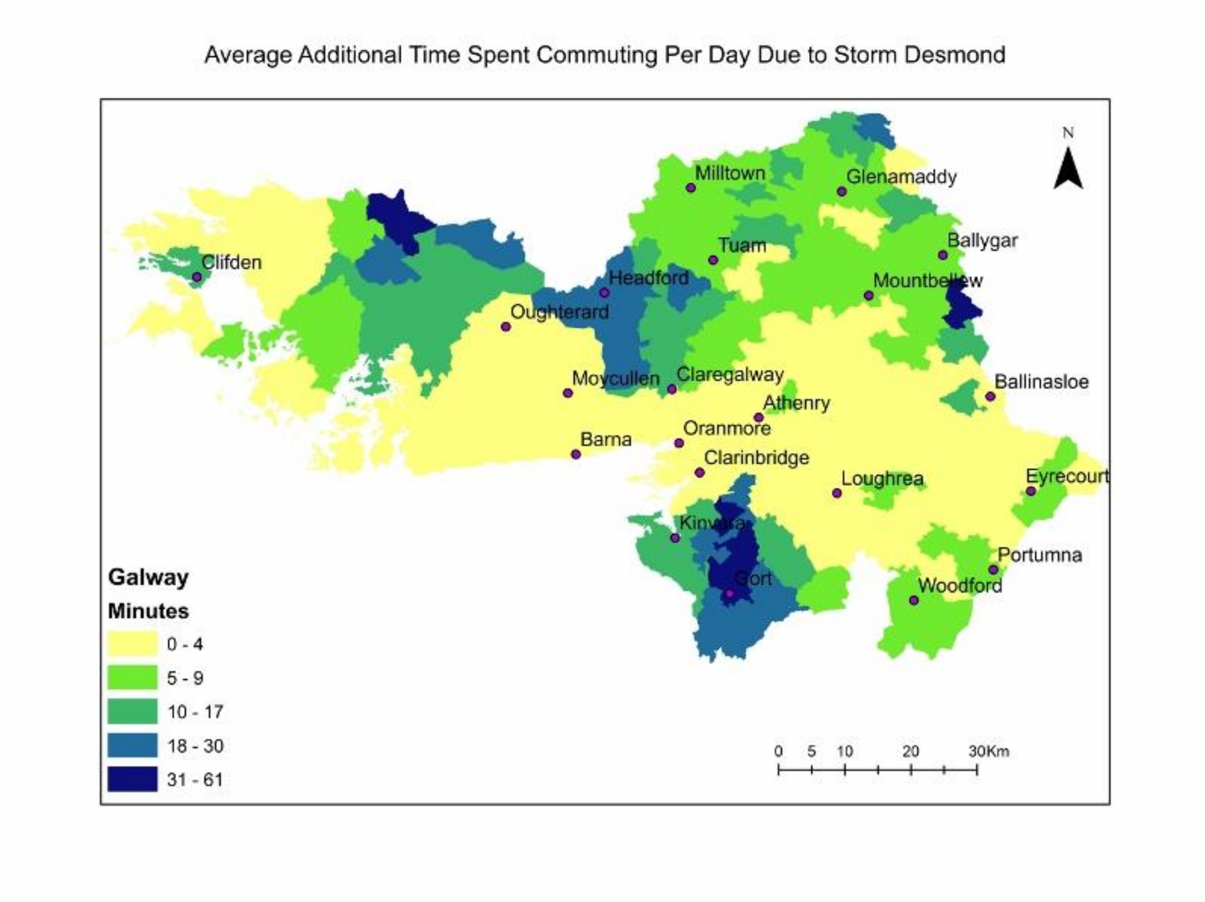
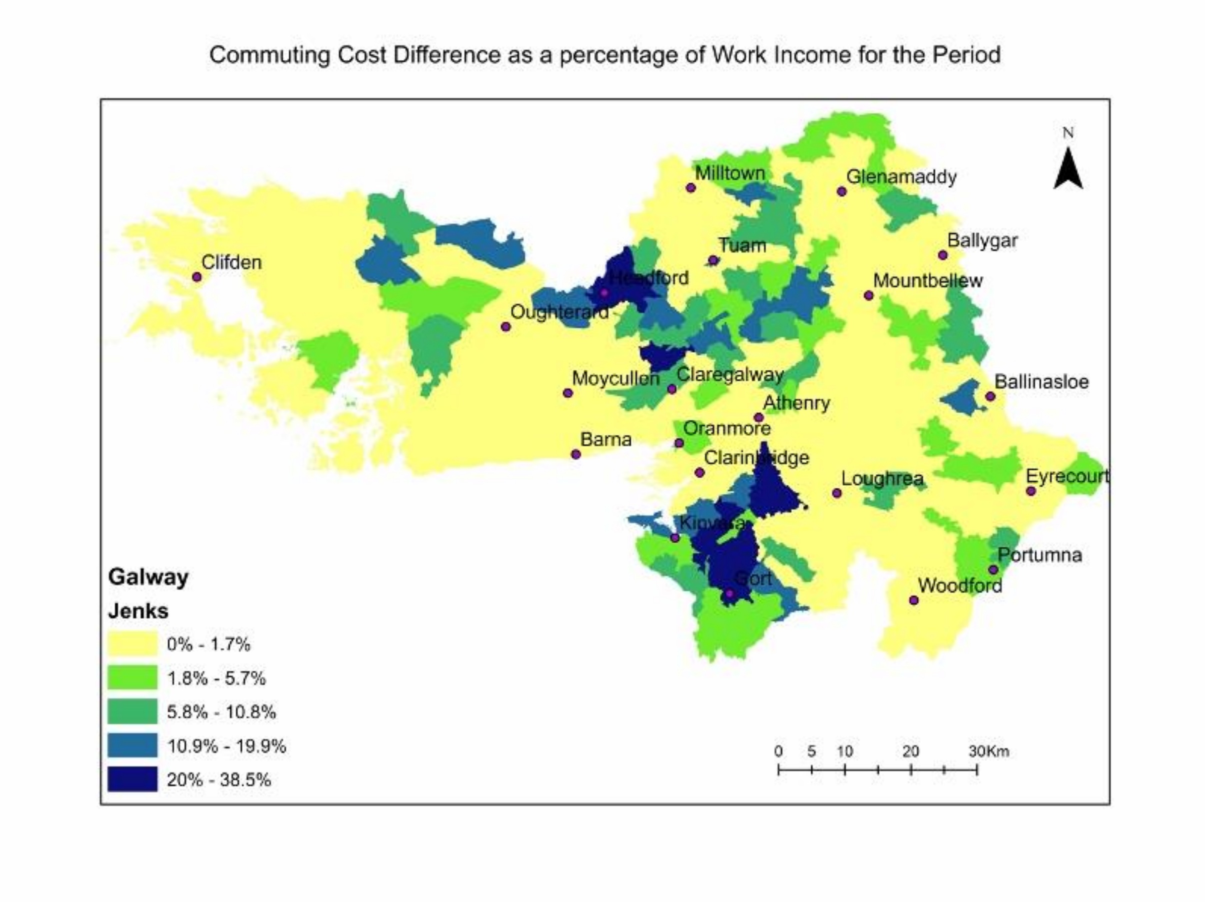


Figure 8-5: Additional time commuting due to floods



When we include the time costs, that is monetary compensation for the extra time spent in your car, the total extra cost of the disruption represents some 10% to 38% of the daily working wage of the average commuter in the worst affected areas [Figure 8-6].

Figure 8-6: Additional commuting costs due to floods as % of work income



On aggregate, we estimate the total cost of the disruption to commuting in Co. Galway during the flooding at €3.8million. This estimate assumes that every commuter in Galway travelled to work each day during the flooding. However, our estimates are conservative in that our model cannot account for delays on non-flooded routes due to additional volumes of traffic, or for disruptions to commuters travelling between Galway and origins/destinations outside the county. We also do not count any costs imposed on commercial vehicles, disruptions to business activity and supply chains.

Results (2) – Distribution of flood impacts

We also investigate the distribution of flood impacts across socio-economic groups, by matching the analysis of commuting costs with individual-level socio-economic characteristics from the SMILE data, e.g. disposable income, age, education etc. Our first set of results, presented in [Table 8-8] shows that people who already have long commutes under the status quo, are disproportionately affected by the flood disruptions. In general, long commutes (under status quo) are associated with higher income, higher education, and being (relatively) young – see column 1 of [Table 8-9]. This same pattern holds for the effects of floods, since effects are increasing in normal commute – see columns 2-5 of [Table 8-9].

However, when looking at commuting costs of flooding as % of disposable income this is decreasing in income (so higher earners are relatively less impacted) – see [Table 8-10]. For every extra €1000 in disposable income, the additional cost of the flood as % of income goes down ~3.6% (see column 1 of Table 8-10). This income effect is even slightly stronger within EDs, at about 4% (see column 2 of Table 8-10). This income effect also holds when controlling for other socio-economic characteristics (age, education, owner occupier) – see columns 3 and 4 of Table 8-10.

Table 8-8: Estimated relationship between time spent commuting under status quo "Total Jtime (norm)" and taking account of the flood disruption "Total Jtime"

	(1)	(2)	(3)
Variables	Total Journey Time (Event)	Δ in Journey Time	Δ Journey Time (%)
Total Journey Time (Normal)	1.155***	0.155***	0.010***
	(0.002)	(0.002)	(0.000)
Observations	39,538	39,538	39,538
R-Squared	0.891	0.127	0.012
Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1			

Table 8-9: Estimated relationship between journey time under status quo (column 1) and taking account of flood disruption (columns 2-5) with various socio-economic characteristics, measured at the individual level

	(1)	(2)	(3)	(4)
Variables	Total Journey Time (Normal)	Total Journey Time (Event)	Δ in Journey Time	Δ Journey Time (%)
Disposable Income ('000)	1.489***	1.943***	0.454***	0.068***
	(0.121)	(0.148)	(0.052)	(0.012)
Age	17.832***	21.468***	3.636***	0.435***
	(1.18)	(1.443)	(0.513)	(0.113)
Age2	-0.190***	-0.228***	-0.038***	-0.003**
	(0.014)	(0.017)	(0.006)	(0.001)
Tertiary Education	17.719***	24.573***	6.854***	-0.042
	(3.866)	(4.728)	(1.682)	(0.371)
Owner Occupier	-36.921***	-49.763***	-12.842***	-3.447***
	(5.679)	(6.944)	(2.47)	(0.545)
Observations	39,538	39,538	39,538	39,538
R-Squared	0.014	0.015	0.006	0.003
Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1				

Table 8-10: Estimated relationship between the change in commuting costs due to flooding (as a % of disposable income) with various socio-economic characteristics, measured at the individual level.

	(1)	(2)	(3)	(4)
Variables	Δ in Journey Cost as % Income	Δ in Journey Cost as % Income	Δ in Journey Cost as % Income	Δ in Journey Cost as % Income
Disposable Income ('000)	-0.0036***	-0.0040***	-0.0040***	-0.0043***
			(0.000)	(0.000)
Age			0.018***	0.012***
			(0.002)	(0.002)
Age2			-0.000***	-0.000***
			(0.000)	(0.000)
Tertiary Education			0.027***	0.029***
			(0.007)	(0.006)
Owner Occupier			-0.043***	0.000
			(0.010)	(0.008)
ED Fixed Effects		YES		YES
Observations	39,538	39,538	39,538	39,538
R-Squared	0.008	0.374	0.01	0.376
Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1				

Table 8-11: Commuter broken down by Urban-Rural Classification

Location	Commuters	% of commuters	Work Income	J time Normal (minutes)	J time Flood (minutes)	Change in J time (minutes)	% Change J time
Rural	9033	0.24	28054	625	738	113	18%
Village (200 – 1499)	5448	0.14	28590	585	742	157	27%
Town (1500 – 2999)	1810	0.05	27968	542	673	131	24%
Town (3000 – 4999)	3492	0.09	25664	374	390	16	4%
Town (5000 – 9999)	2544	0.07	29326	570	649	79	14%
Galway City	15833	0.41	26791	228	238	10	4%

Table 8-11 shows the breakdown of commuters by urban-rural classification. As you would expect most commuters live in Galway city. Surprisingly rural commuters have a higher level of disposable income compared to those in more urban areas. This however may be offset when we consider their much greater journey times on average. Over 400 minutes longer compared to a Galway city commuter over the 17 day period.

Table 8-12: Theil Decomposition Index of Inequality, showing market work income plus travel costs before and after the flood event

Period Income and Costs	Within Area	Between Areas	I_2 Index	Within %	Between %	Gini	Reynolds-Smolensky
Market Work Income	0.235	0.060	0.293	80.2%	20.3%	0.327	0
Normal Scenario:							
Monetary cost travel	0.314	0.074	0.386	81.3%	19.2%	0.361	-0.034
Time cost travel	0.259	0.063	0.321	80.9%	19.7%	0.340	-0.012
Total cost of travel	0.359	0.083	0.439	81.7%	18.9%	0.377	-0.050
After Flooding:							
Monetary cost travel	0.328	0.078	0.403	81.2%	19.3%	0.364	-0.037
Time cost travel	0.263	0.064	0.326	80.9%	19.6%	0.341	-0.013
Total cost of travel	0.385	0.091	0.473	81.4%	19.2%	0.383	-0.056

On quantifying the impacts of flooding it is beneficial to examine how commuting and more important in this case the disruption effects on flooding. Table 8-12 shows the Theil index measures. We observe how commuting and the flood disruption have increased the overall level of inequality. The monetary cost of travel has a greater impact on inequality compared to the time costs. Overall commuting is extremely regressive increasing inequality from 0.293 when we consider work income, up to 0.473 after commuting and the flood disruption. As in most cases more of the variation in incomes and costs can be explained between individuals rather than between areas. This would suggest a large variation in travel times and distances within an area. This trend holds for commuting before and after the travel disruption. The increased Gini coefficient confirms the regressive nature of commuting and the disruption.

Figure 8-7: Lorenz Curves of work income for the 17 day period before and after commuting, including flood disruption

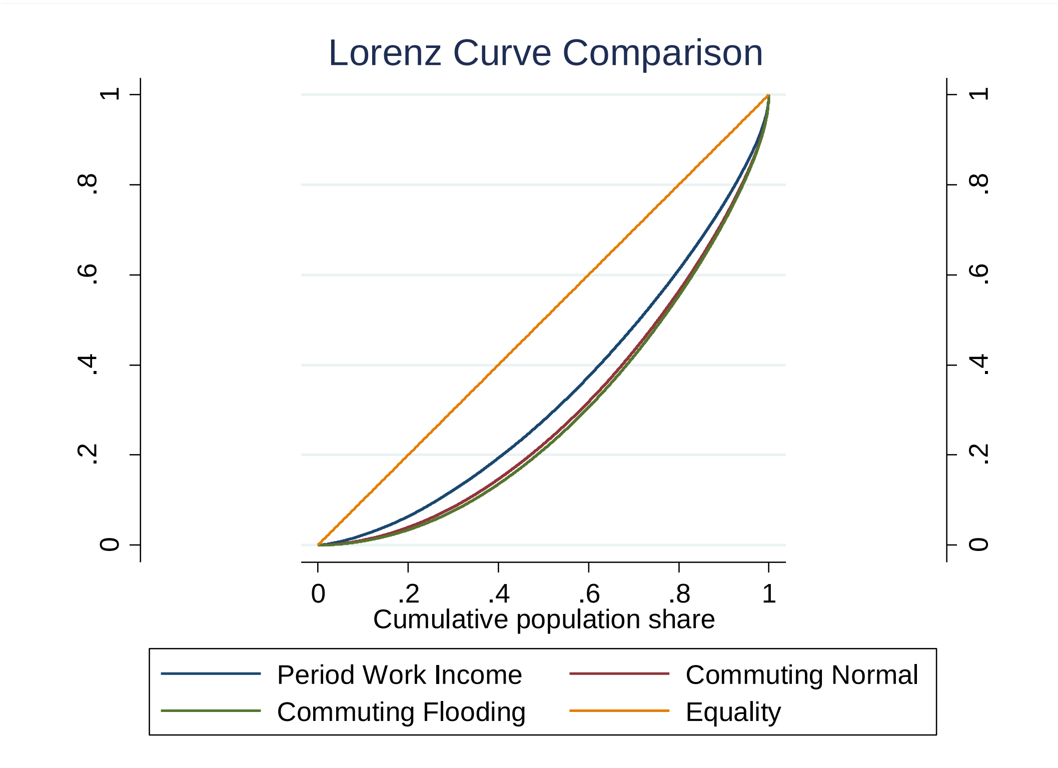


Figure 8-7 combined with Table 8-13 gives us a greater understand of how this increased inequality impacts on the income distribution. Figure 8-7 shows the shifting out of the Lorenz curve after the inclusion of commuting costs, the curve shifts out again even further when the disruption is considered. Notice also how the gap decreases further up the income distribution, illustrating how poorer individuals are discretionally impacted by the disruption. Table 8-13 further supports this point as we can see that the impact of commuting is felt greater in the lower quintile groups. This impact levels off around the 6th decile at which point the percentage share of income starts to increase. The increased burden of commuting and costs associated with disruption are disproportionally felt at the lower end of the income distribution.

Table 8-13: Percentage Share of Income attributed to each quintile group

	Period Income		Commuting		Commuting After Flood	
Quintile Group	% of Median	Share %	% of Median	Share %	% of Median	Share %
1	37	2.3	24	1.2	20	0.9
2	55	4.1	43	2.7	39	2.5
3	72	6.0	62	4.5	59	4.2
4	85	6.9	82	6.2	80	6.0
5	100	8.4	100	7.8	100	7.7
6	116	9.7	120	9.4	121	9.4
7	131	11.1	143	11.3	145	11.3
8	149	12.6	168	13.3	172	13.5
9	179	14.6	210	16.0	216	16.3
10		24.2		27.7		28.3

8.7 Conclusions

It is clear given our analysis that flooding has had a significant impact on commuting costs. The total aggregate cost of extra time and distance commuting is €3.8 million. Our results should be taken as conservative estimates; the true impact could be considerably more when we account for non-recurrent congestion and the wider impact cross-boundary. The costs associated with the disruption are unequally distributed across income groups. Those already with large commuting costs are burdened with extra costs. In areas particularly badly affected, extra costs amount to 39% of earnings (during the period of disruption). This has had an inequality increasing impact across income groups. Those on lower incomes suffer proportionately greater losses. Those living in rural areas are more at risk travel disruptions given their longer on average commuting times. These areas are also served poorly by public transport so have no alternative to using the car.

Given the large number of National roads affected more infrastructure advancements should be made to ensure the road network is more resilient to extreme weather events such as this. Councils should ensure that the main arteries which connect places of work and residence be kept open. A similar type vulnerability analysis should be conducted (Jenelius and Mattsson, 2012). More planning considerations should be given towards reducing commuting times, whether that is through increased public transport provision or reducing the distance between areas of residence and areas of work. More flexible working arrangements could also be put in place whereby workers affected could work from home if possible. Given the large number of rural commuter impacted this may not be possible due to poor broadband coverage. This would have an opposite impact and in fact save commuters money (Caulfield, 2015).

This paper makes use of advanced commuting models, spatially rich flooding data and simulated income data. It illustrates a method whereby the indirect costs of extreme weather events can be measured. In the aftermath of future events it should be possible to makes estimates around costs to commuters, something which is often previously ignored. This paper also highlights the vulnerability of car users to environmental shocks. This is compounded even further when there is a lack of transport alternatives available in an area.

Chapter 9. Thesis Conclusion

9.1 Introduction

This research aimed to examine welfare in a spatial context. The definitional approach applied to welfare was an important aspect of this thesis. Typically income, more specifically disposable income, is used as a proxy for welfare. There are however aspects other than income which will impact on an individual’s potential to consume and thus increase/decrease their level of welfare (Atkinson, 1983, Barr, 1998, Frey and Stutzer, 2002). While there are a significant number of studies which have examined the impact of these drivers on welfare, they have been at an aspatial scale. This thesis fills a number of gaps in this regard, firstly using a broader definition of welfare and secondly examining this broader definition of welfare at a detailed spatial scale.

Studies with the aim of measuring welfare across space have been limited, largely due to a lack of detailed spatial data on income. Using the output from a spatial microsimulation model presented a spatially disaggregated measure of income and aided in overcoming the issues of; a lack of income information in census data and a lack of spatial information in survey data. Using a spatial distribution of disposable income created using synthetic data from SMILE as a base measure of welfare enabled the effect of additional welfare measures on the distribution of welfare to be estimated. The sensitivity of spatial welfare to the drivers of welfare was examined. Drivers of welfare included; intertemporal effects, income from consumer durables such as housing, time lost due to commuting, impact of labour markets, effects of climate change and utility gained from spatial attributes. These aspects impact on individual welfare and are included in the comprehensive measure of welfare presented here.

Welfare consists of a range of monetary and non-monetary measures. These measures are not homogenous and will therefore vary across place. Levels of income, housing costs, commuting times, local labour markets and amenities all vary spatially. Individual’s attempt to trade-off these aspects of welfare against each other when deciding where to live and work. When considering these additional drivers of welfare, it is important to measure them spatially. The methodologies used in this thesis have made that possible. The drivers of welfare examined in this thesis were all calculated at the ED level.

The SMILE model was updated with the use of spatial methods such as kriging and network analysis to include additional welfare data. This additional spatially rich data was created using spatial methods before being combined with the microsimulated dataset from SMILE. A range of welfare drivers such as commuting, housing, local labour markets, spatial attributes and flooding were then examined in a spatial context. Taking a spatial approach, allows welfare to be examined both between and within area. The characteristics of these areas can also be summarised using the welfare measure to differentiate and contrast areas. The year of this research is 2011 as this is the most recent year for which SMILE income data is available.

9.2 Summary of Findings

This thesis took a holistic view of welfare and aimed to examine different drivers of welfare at a detailed spatial scale. The results and findings of the thesis support the general consensus that welfare varies considerably across place. Differences in both between areas and within areas between people were found, with much of the variation occurring within rather than between areas. Utilising different definitions of welfare and calculating the spatial distribution of welfare before and after the addition of each measure, has enabled the sensitivity of the spatial distribution to the addition of each measure to be examined. The impact of the additional drivers of welfare highlights the importance of using a comprehensive definition of welfare. More than just income will impact on individual welfare, other monetary and non-monetary components should be considered. Adopting a broader definition of welfare will have implications of inequality and poverty analysis in Ireland at a detailed spatial scale.

The rest of this section is as follows, the next section discusses the major findings and contributions of the various papers. There is a reflection on the PhD and thesis approach, with critical analysis of methodologies and data used. The importance and relevance of the thesis findings for policy are highlighted. Follow on and potential further research is then listed. Finally all dissemination and research outputs and impacts are documented.

Chapter 3 discovered an increase in concentration of high incomes in and around Dublin City. Urban areas are vastly outperforming rural areas in terms of income. There is an increasing regional imbalance between urban and rural areas. This gap has increased during the time period examined in this paper (1996-2011). The statistics of the areas in the bottom quintile, which are largely rural, are not promising. These areas are characterised by high levels of unemployment, low income and low levels of third level education (see chapter 6 for examination of vulnerable areas). Equally there may be non-monetary reasons why individuals are choosing to live in these areas, such as better amenities and a better lifestyle/environment (chapter 7). What the results have shown is that current regional policy is failing. Government has failed to control the concentration of economic activity around the GDA. The trends are worrying and have already led to a housing crisis particularly in the GDA (as described in Chapter 4). This crisis was inevitable given the increasing wages and property prices in these areas. Attractive living conditions; good services, high wages; have led to permanent differences in the wage and unemployment rate. It is difficult for income to increase in an area of high unemployment due to the excess in labour supply; therefore the districts with the lowest incomes also tend to be the districts with the highest levels of unemployment. There is a spatial concentration of those most at risk of poverty. Centrifugal forces include high rents (chapter 4), commuting (chapter 5) which then leads to congestion and supply of immobile factors (Fujita *et al*., 2001) while centripetal include local labour markets (chapter 6) and higher incomes (chapter 3).

Chapter 4 has shown the value of including in-kind benefits into the calculation of disposable income. By ignoring these variables we are not measuring the full costs and benefits which households experience. When we take into account housing costs in the form of rents and mortgage payments; and housing benefits in the form of imputed rent and reverse mortgage annuities, the spatial distribution of income changes. On average the wealth of the GDA increases however when we examine the movers more closely the high rents and property values in the GDA are masking the high costs young workers are facing. The differences in housing costs spatially have a greater impact in areas where property values are high. These high property values, particularly in the GDA, can lead to higher benefits from housing but also higher housing costs. The inequality measures have shown that overall housing costs and benefits are having a regressive impact on the income distribution. This however is not the case for all age groups and the benefits for older age categories are clear to see. Reverse mortgage annuity has great potential for those who are 65+. Perhaps people should view reverse mortgage as a type of pension which they have paid into over the term of the mortgage. They can then draw down this pension upon retirement.

Chapter 5 highlighted how the increasing numbers employed in professional and managerial posts in the GDA and other Irish cities has led to higher salaries in these areas (Morrissey and O'Donoghue, 2011). At the same time, levels of commuting increased across the country, particularly in the GDA (Commins and Nolan, 2011, Vega and Reynolds-Feighan, 2009). This was accompanied by significant investments in transport infrastructure, which have primarily focused on public transport improvements in the GDA and the development of the inter-urban motorway network (Vega and Reynolds-Feighan, 2012). Incorporating data from a spatial microsimulation model within a travel demand model, it was found that while there is a relatively better provision of transport infrastructure in the GDA than in the rest of the country, the net cost of commuting in this region is significantly higher. This is particularly evident in the case of the commuter counties adjacent to Dublin City, which also present some of the highest levels of average income in the country. This paper shows that in the case of the GDA, higher income levels do not compensate for the cost commuting in these areas, which results in a relative drop in the county level income ranking. Further analysis found that other Irish cities show high net commuting costs as a percentage of income, in particular Galway City and its commuter hinterland. In contrast, the relative impact of commuting on employment income is significantly lower outside the primary commuting belts, particularly smaller towns and rural areas.

Chapter 6 it was found that while a number of farms can generate viable returns, the returns from farming provide only a relatively modest income. These results are very sensitive to the presence of agricultural subsidies. For most of the country farming is sustainable, however largely due to the availability of off-farm employment. The economic downturn which has brought reduced employment, particularly in areas where farmers traditionally find work, such as construction pose serious risks for sustainability. Lastly, the areas with higher proportions of unsustainable farms tend to be in areas outside the commuting zones which even during economically prosperous years pose demands for rural development policy to improve the economic sustainability of these areas.

It is particularly the areas which have the highest levels of unemployment that are of greatest concern. Unlike in the areas of high unemployment not classified as vulnerable, workers cannot simply be re-trained and re-skilled. Very often these areas are coming from a low base of education and training. ~50% of individuals are unskilled workers.

These areas are particularly vulnerable. The lack of growth in these areas can also have knock-on generational effects. The lack of opportunities whether in farming or off-farm employment, acts as a disincentive for future generations to remain in these areas and increase the levels of outward migration.

One of the biggest future challenges to rural policy will be in relation to farming areas in close proximity to major economic centres. There is a growing need to redefine what we mean by rural. Rural varies between areas that are close to urban areas which are more resilient compared to remote rural areas which are vulnerable to economic conditions. Rural policy 3.0 (OECD, 2016d) policy framework moves beyond farming and subsidising specific sectors towards making rural areas more competitive. This new approach also recognises the fact that there are different types of rural areas. It recognises the opportunities that exist in rural areas outside of agriculture. Rural areas with a higher quality of life but lower wages can attract and hold onto workers and their families.

Chapter 7 reinforces previous findings; that monetary income is not a good predictor of welfare. When we include a measure of life satisfaction into our analysis the richest areas in terms of monetary wealth no longer have the highest levels of welfare. We witnessed a shift from major urban areas to rural areas and areas where there was less urbanisation. The inclusion of the environmental attributes highlights the importance individuals place on location. The spatial distribution of welfare depends upon the definition of welfare we use. If disposable income is used as a proxy for welfare, those areas with the highest earners fare well. If however we consider other non-monetary characteristics such as climate and environmental variables the spatial distribution changes dramatically. The majority of inequality in welfare occurs within rather than between districts. This important finding may warrant further investigation.

The results show that living in an urban environment is not necessarily the best to have a high level of life satisfaction. The pressure and stress of education, employment and income demands can have a negative impact on mental health. Our results emphasise the importance individuals place on environmental characteristics and attributes, measures which are often ignored with measuring the deprivation or poverty in areas. Concentrating economic activity in urban areas may not be the best solution if the goal is to improve individual’s overall levels of life satisfaction. What is clear is that individuals are willing to forgo extra income to have better life satisfaction and higher levels of welfare. Not all rural areas however report high levels of welfare. This suggests the issue is more complicated than simply living in a rural area beside the coast.

Chapter 8 showed that flooding has had a significant impact on commuting costs. The total aggregate cost of extra time and distance commuting is €3.8 million. Our results should be taken as conservative estimates; the true impact could be considerably more when we account for non-recurrent congestion and the wider impact cross-boundary. The costs associated with the disruption are unequally distributed across income groups. Those already with large commuting costs are burdened with extra costs. In areas particularly badly affected, extra costs amount to 39% of earnings (during the period of disruption). This has had an inequality increasing impact across income groups. Those on lower incomes suffer proportionately greater losses. Those living in rural areas are more at risk travel disruptions given their longer on average commuting times. These areas are also served poorly by public transport so have no alternative to using the car. This paper highlights the vulnerability of car users to environmental shocks. This is compounded even further when there is a lack of transport alternatives available in an area.

9.3 Overall Conclusions

What is clear from the analysis presented in this thesis is that traditional economic measures used to measure the welfare of society are not capturing all direct and indirect impacts on welfare. The spatial distribution of welfare changes depending upon the definition of welfare used. This highlights the amount of spatial heterogeneity that exists in welfare. It is clear that by taking a broader definition of welfare to include a wider range of measures such as commuting, housing, local labour markets, exposure and life satisfaction more of the variation in welfare is explained. The more information which is included at a spatially disaggregated level, the more accurate the findings will be. This is crucial as it will be these findings upon which policy makers base planning decisions.

A clear example of this is in the GDA which has the highest levels of disposable income. Including commuting costs however changes this spatial distribution of welfare. The high levels of disposable income witnessed previously are now offset by high commuting costs. When housing costs and benefits are included there is a similar result. Higher wages in urban areas do not appear to be compensating for the higher living costs faced. Individuals appear to find it difficult to take into consideration the longer commute times, high levels of congestion and also the higher rental and property prices associated with urban living. The level of complexity around weighing up earnings, commuting costs, time costs, housing costs, housing benefits, spatial attributes, access to services, quality of life and labour market opportunities is high. This makes it difficult for individuals to make efficient decisions.

Intertemporal

The intertemporal welfare analysis identified a trend of increasing concentration of high income households in the GDA area. During this period there was a move away from manual towards more professional industries. This is largely due to the increasing levels of education attainment over the same period. Poor levels of job opportunities in small/medium towns and rural areas has led to migration and increased concentration in cities. High skilled workers are more likely to find employment in concentrated labour markets. This increase in concertation however has had negative side-effects and increasing inefficiencies such as in housing and commuting.

Housing

It is not surprising that the highest house prices are in the GDA given the increased level of concentration there since 1996. Nationally there are low levels of home ownership among those aged 50 and under, as a consequence of this low level of home ownership there are high numbers of 15-35 year olds renting privately (~1 in 3 households). The structure of home ownership in Ireland is undergoing significant change, high private rents and increasing property values have had a large impact on the redistribution of populations in Ireland. This is especially the case in the GDA which has witnessed the greatest levels of increase in house prices. The lower than average level of home ownership in the GDA suggests issues around affordability compared to rural areas. In contrast to the younger generation, levels of home ownership amongst the elderly are very high. The elderly benefit significantly from owner occupation through imputed rent and potential annuity payments. Although housing benefits reduce overall inequality in the economy, the Lorenz curves cross. The effects of owner occupation are felt disproportionately.

Commuting

Improvements are required to reduce commuting times and costs. One solution is to reduce the distance between place of residence and place of work. This can improve efficiencies and reduce commuting times and costs. Technological progress makes it possible for workers to be as productive working from home. This eliminates the commute and reduces the requirement to live close to work. If the place of work is in an urban environment this is often associated with high housing costs. Other options such as creation of regional hubs of employment where surrounding property prices would be lower and commuting times lower compared to urban centres. The spatial distribution of welfare using life-satisfaction as a proxy shows that those working in cities may not necessarily be happy. They may have had to move to a city as the employment opportunities are better, particularly workers with high-skills. The main problem appears to be one of choice. Workers are concentrating in the GDA due to the lack of employment opportunities elsewhere. This is leading to increasing inefficiencies such as congestion and higher house prices. The continued policies that drive this concentration are not benefiting overall levels of welfare.

Local Labour Markets

Classifications of farm viability are spatially concentrated with farm viability located below an imaginary line from Dundalk to Limerick. Areas which are sustainable rely heavily on off-farm employment. Although farming in these areas is not very profitable, they benefit from their close proximity to job opportunities and good local labour markets. Due to the remoteness of the vulnerable areas they do not have the advantage of these local labour markets. These areas are characterised by having a below average skills base and high unemployment. The problems in these areas are structural and will require targeted resources. The future challenge for rural areas and agriculture is keeping high-skilled workers in these areas by providing them with job opportunities in close proximity. A strategy aimed at creating more spatially dispersed high-skilled employment will also reduce the increasing level of concentration in the GDA and ease the pressure on transport networks and housing demand.

In terms of rural development there are significant challenges facing the economic viability of agriculture. Population centres grew up around most productive agricultural areas. However over the last number of decades there has been a move away from agriculture into IT, biomedical etc. Farming no longer appears attractive anymore as the alternatives in these areas offer a better quality of life. This leads to increased pressures on land, for leisure and housing which may not be sustainable in the future as there is still a need to produce food; particularly locally as there is increasing focus on emission targets and food transport. The analysis highlights the reliance of agriculture on outside funding sources without which it would not be economically viable.

Non-monetary Welfare

The contrast between the spatial distribution of welfare using disposable income and life-satisfaction highlights the value of place. The monetary distribution and non-monetary distribution vary significantly. There is a shift away from Dublin towards the south coast. Spatial welfare using life-satisfaction as a proxy follows a similar Dundalk to Limerick line. The high commuting costs, high housing costs and high incomes did not result in high welfare. This would suggest that people may be willing to forgo extra income for a better quality of life. After life satisfaction is considered, urban areas perform quite poorly and experience low levels of welfare. This highlights the value people place on environmental attributes and the amenities of a region or area. You might expect these tributes to be included in property prices however does not appear to be the case. The areas which have the highest levels of welfare are not the same areas which have the highest levels of disposable income and property values. Further research is required to examine the reasons behind why those in the GDA remain, despite reporting low levels of welfare?

Climate Change

The analysis of the flood event shows that commuting has a regressive outcome on the income distribution with those on lower incomes especially vulnerable. This study however only measures the indirect costs. There are other non-monetary costs as a result of a flooding event such as increased stress. Given the increased risks of flooding due to climate change the raises some questions around who the most vulnerable groups are?

Concluding Remarks

Conducting an analysis of space with a broader definition of welfare makes it possible to answer questions around how policy decisions impact spatially. Results from this analysis will provide solutions and recommendations based on detailed spatial analysis and geo-demographics. It is the hope that this thesis will highlight the benefit of detailed spatial analysis in an Irish policy context.

Small area analysis plays an important role urban and rural policy. Spatial analysis is used to identify areas which require government intervention due to increasing levels of poverty, increasing congestion or over reliance on a specific industry. Geo-demographics can measure whether the capacity of the medical or education system, or public transport infrastructure will be sufficient in serving future populations. Adopting a broader definition of welfare identifies the impact of space on welfare and where welfare losses can be improved.

9.4 Reflections

Overall Reflections

The thesis has provided a comprehensive analysis of the spatial distribution of welfare and its drivers. A more comprehensive definition of welfare has been used in this thesis to account for differences over time and space. These spatial differences and more specifically their examination at a spatially disaggregated level is the main contribution of this thesis.

Some of the more complex social realities cannot be fully captured in economically framed geo-spatial modelling. This is especially the case for those who effectively fall outside of the economic systems of welfare examined here and who become welfare dependants within the system.

The various papers have complemented each other. Each chapter introduced a new spatial driver of welfare and estimated its impact on welfare. The most important spatial drivers of welfare are examined; income, housing, commuting, labour markets, happiness, spatial attributes and environmental hazards. The methodological framework used means additional spatial drivers can be added and examined at a later date. Some of these additional drivers such as recreational facilities are discussed as next steps for this research.

This thesis has taken an interdisciplinary (economics, geography and geocomputation) approach towards the measuring of welfare. Spatial microsimulation, kriging, network analysis, entropy measurement, GIS and self-reported life-satisfaction are just some of the methodologies taken from various disciplines. They highlight the importance of how beneficial it can be to learn and apply methods from other disciplines.

Personal Development reflections

In terms of research impact and reach, the papers which are published in peer reviewed journals are available ResearchGate. This allows the author to track reads by other ResearchGate members. It is possible to see who has read the article (name, country, institution) and also whether they read the full article or just the abstract and introduction. The paper "The Spatial Impact of Commuting on Income: a Spatial Microsimulation Approach" has 1 citation, 2 shares and 143 downloads on the Springer website and 83 reads and 1 citation on ResearchGate. This paper also received some attention in the national press appearing in the Irish Times (Siggins, 2016). The paper "Intertemporal Income in Ireland 1996-2011–A Spatial Analysis" has 75 reads and 3 recommendations on ResearchGate and 7 downloads and 26 abstract views on IDEAS - RePEc[43]. Using sites such as ResearchGate and IDEAS allows the research to track the impact and reach of their research. It is possible to identify researchers from other institutions who are interested in your work and increases opportunities for collaboration. They provide young researchers with powerful tools to promote their research.

Publication Process

In regards to the publication process, overall I found the process challenging and rewarding. Before writing the final draft of the paper a journal was chosen which would closely match the paper. As I had recently presented at the IMA's International Meeting (Oct. 2015) I decided to submit that paper for the conference's special issue. The first paper I submitted "intertemporal income in Ireland" required some major revisions particularly in the results and conclusion sections which had to be rewritten before re-submission. The review process can be quite slow, although given the fact that referees carry out this work on top of their own day job, this is completely understandable. It was interesting in receiving the feedback from referees to notice the two different styles adopted. Referee 1 giving deep insight into where the paper should concentrate more on and how this could be approached, whereas referee 2 was more specific and concentrated in their comments, asking specific questions on material written in the document.

[43] All read and download statistics correct as of 15/08/2017

Data

Some of the analysis in this these has been limited by the data utilised. The year 2011 was used as this was the most recent year at the time of writing for which small area income information was available. For this reason each paper represents an analysis of the spatial distribution of welfare for that given year. However due to the unique nature of the analysis conducted the results and conclusions remain the most recent results at this level of spatial disaggregation. Given the structure of the methodology used this analysis can be easily updated when new more relevant data becomes available.

In calculating travel times and distances the best available data on the road network came from the open source database OpenStreetMap. One of the challenges in calculating a travel time and travel distance is trying to account for congestion. There is little detailed spatial information on traffic volumes publicly available in Ireland. The National Roads Authority publishes daily traffic volumes at a number of points however there is not enough information to accurately predict the level of congestion on all routes. One of the limitations of the commuting study has been the lack of detailed congestion data. The speeds from a Road Safety Authority free-speed survey were used in attempting to account for congestion. This survey reported the average speed of cars broken down by road class.

A lack of spatially detailed house price data was one of the major limitations in chapter 4. BER data contains rich house attribute data however is not publically available and does not contain information on value. The PPR contains house sale price data but no housing attribute data. This register only dates back to 2010 and is not geocoded only containing the address of the property. To overcome this issue national average house price data from the Department of the Environment was used and estimated at a county level using Daft.ie estimates and at an ED level following the same pattern as the rental values estimated using the kriging methodology. While this approach is not without its limitations; it accounts for spatial differences in house prices. As the Department of the Environment data dates back to 1971 a time span not found in any other house price dataset.

SMILE model

The SMILE methodology has enabled income at a detailed spatial scale to be estimated. This income model has then been extended to include other non-monetary and benefit in-kind aspects of welfare to be measured and included in the spatial distribution of disposable income. Extending this model to include intertemporal, housing, commuting, agriculture, flooding and climate change exposure. There are however some limitations to microsimulated data. Neighbourhood effects can never truly be captured.

Despite this spatial microsimulation has helped to overcome the problem of, a lack of income data at a detailed spatial scale. Using aggregate county level incomes you would not be able to identify small pockets of low or high welfare as you do not have the same degree of spatial disaggregation. Similarly using survey data, although you would have more individual level data, the data does not have a spatial component. Although spatial microsimulation has some limitations, it is simulated data, it will not match what is observed in the real world perfectly, it has aided in overcoming a limitation which has hampered many studies. Without the spatial distribution of income and detailed dataset from SMILE, it would not have been possible to examine the drivers of welfare spatially.

9.5 Policy Recommendations

The results from the analysis highlight a number of main findings:

- There is a concentration in economic activity in the GDA
- Housing impacts on income groups disproportionally
- Higher income levels in urban areas do not compensate for the cost commuting
- Access to local labour markets is impacting on viability of rural areas
- Higher incomes does not necessarily equate with higher levels of welfare
- Flooding disruptions impact on the poor disproportionately, highlights vulnerability of car users

The results from the analysis can contribute to spatial policy in Ireland in particular the forthcoming National Planning Framework (NPF, 2017) and Action Plan for Rural Development (Rural Ireland, 2017) strategies. Special focus should be given to the main findings highlighted above.

This thesis presents a spatially refined measure of welfare previously not available. The methodologies employed in this thesis can be used to recreate the spatial distribution of welfare using the recently released Census SAPS for 2016. This would present the first intertemporal analysis of spatial welfare using the additional components of commuting, housing, labour markets and spatial attributes.

Reducing Inequality & Poverty

The increasing concentration around the GDA is of growing concern. High wages are unable to compensate workers for increasing commuting and housing costs. High skilled individuals are attracted to concentrated labour markets as there are more opportunities. Given the increasing level of education attainment in Ireland, better job opportunities are required outside of the GDA. A strategy aimed at creating more spatially dispersed high-skilled employment can help in reducing the increasing level of concentration in the GDA and ease the pressure on transport networks and housing demand.

Using spatial analysis has the potential to benefit in combatting the problem of low employment opportunities. Using SAPS current and projected trends of education attainment, optimised locations in which to develop employment hubs can be identified. Locations are selected based on maximising the potential number of employees within a particular radius. Such an approach can be useful in pooling labour into new labour markets and improve opportunities in these areas especially for high skilled workers. Individuals in these largely rural areas are given a choice of working in their native area as opposed to migrating to an urban environment.

Given the level of technological progress these new employment hubs can provide hot desk facilities to workers. These workers may work from this location for the majority of their working week. Regional employment hubs provide the opportunity to live and work in an area with high spatial attributes, low congestion and affordable housing costs. It is possible for workers in different industries and companies to locate in the same hub which can harness innovation and collaboration. These employment hubs are an improvement on working remotely from home as they provide increased social interaction. Initiatives such as the Gigabit Hub and HQTralee are welcome additions in this regard.

Rural development policy should be aimed at the areas which do not have the same clear natural advantage such as the areas classified as vulnerable. Given the large reduction in communication costs there are new opportunities to use technology to reach new markets. Improved communication networks have reduced the importance of geography. The move away from manufacturing industries results in firms no longer having to locate close to raw materials or suppliers. The main reason behind a firm locating in a city location is to take advantage of the skilled labour force.

The high rental values particularly in the GDA may hinder an individual's ability to save for a mortgage. They also face the reality of higher house prices compared to other areas of the country. Options to provide more subsidised rental accommodation in the GDA should be investigated. This can improve an individual's ability to save by providing more disposable income.

Tax Imputed Rent

It would be worthwhile to examine a tax on imputed rent which would go towards reducing the inequality between those who own a house and those who are renting. This would be an improvement over the current LPT which is levied on all properties despite the fact private renters do not receive the same level of benefits from housing as owner occupiers. The income brought in from such a tax may then be used to provide subsidised rental accommodation. More analysis is required around the implications such a tax may have on the income distribution and as a disincentive towards owner occupation.

Data

One of the biggest requirements in conducting empirical analysis is the underlying data. Having collated data in a number of fields it is clear that the best most accurate information is not often available.

With the growing popularity of smart phones, android users (providing they have location services turned on) leave behind a trace of the journeys they take. This information is fed back into servers to give users of map applications accurate journey time estimations which accounts for congestion. It is able to use historic data to predict at a particular time how long a journey will take. This raises a serious question in regards to this data currently being collected and used for commercial purposes and whether it should be used for the "public good". Making this data available to researchers (abiding by confidentiality agreements) would provide information rich data resulting in more accurate findings.

The Property Price Register (PPR) was a welcome addition when launched in 2010. The database contains every house sale in Ireland since 2010. It was the first publically available database on final property sale prices. The PPR gives some detail in regard to the postal address, sale date and price of property. It contains no more information however about the property's characteristics and attributes. One criticism around the PPR is the lack of accuracy regarding the address. A close inspection of the data reveals spelling mistakes in the address fields. This makes any fuzzy string match methods difficult to perform. It would appear that the level of validation taking place is low which raises questions around its accuracy. Two years after the launch of the Eircode, there is no Eircode field listed in the PPR database. This makes matching across datasets difficult and very problematic as there is no unique identifier. Any linking across datasets relies upon string matching. More collaboration and joined up thinking is required in the area of data collection in Ireland. Simply solutions such as the inclusion of the Eircode in various property datasets simplifies the linking of datasets.

The price of property does not strictly follow geographical boundaries therefore it would be incorrect to assume it does. Any information that is presented in the media or policy reports normally lists property prices by county. The price of property is a combination of location and house characteristics. Adopting a methodology such as kriging can help in data smoothing property prices so that they do not strictly follow boundaries. Given the current housing crisis more spatially disaggregated units should be used to inform policy decisions. These should be applied for social security payments such as the Housing Assistance Payment (HAP).

A new geographical unit should divide the country into urban zones or commuter belts. There is an urgent need for a Dublin metropolitan area boundary as there are large disparities between the Greater Dublin Area and other major cities such as Galway, Limerick, Cork and Waterford. The GDA is becoming an outlier. Current geographical divisions run into issues such as the Modifiable Aerial Unit Problem (Openshaw, 1984)

Geo-Demographics

The intertemporal analysis has shown how small area socio-demographic and economic analysis can aid in planning for the future. The growing level of educational attainment and move away from manual industries required an increase in the number of high-skilled job opportunities. The concentration of economic activity led to a dense labour market proving attractive to high-skilled workers. This spatial concentration combined with high housing costs has led to increasing levels of urban sprawl. Given the forthcoming NPF, ongoing geo-demographics analysis is of crucial importance to try and prevent future mistakes from occurring. Potential problems can be identified before they become current problems.

Building Resilience

Given the large number of National roads affected more infrastructure advancements should be made to ensure the road network is more resilient to extreme weather events such as flooding. Councils should ensure that the main arteries which connect places of work and residence be kept open. A similar type of vulnerability analysis should be conducted (Jenelius and Mattsson, 2012). More planning considerations should be given towards reducing commuting times, either through increased public transport provision or reducing the distance between areas of residence and areas of work. More flexible working arrangements could also be put in place whereby workers affected could work from home if possible. Given the large number of rural commuter impacted due to flooding, this solution may not apply to all due to poor broadband coverage. Working from home can save commuters money (Caulfield, 2015). This paper makes use of advanced commuting models, spatially rich flooding data and simulated income data. It illustrates a method whereby the indirect costs of extreme weather events can be measured. In the aftermath of future events it should be possible to makes estimates around costs to commuters, something which is often previously ignored.

9.6 Contributions to the literature

This thesis has contributed in a number of ways to the literature. These contributions are summarised as follows:

- Conducted an intertemporal analysis of disposable income in Ireland at a detailed spatial scale.

- Estimation of a net imputed rent and the impact on the income distribution calculated at a small area level.

- Calculated the impact of commuting, both monetary and time costs, on employment income at a small area level.

- Examined the characteristics of the areas of farm viability. Identified pockets of extreme farm vulnerability where resources can be targeted.

- Highlighted the large differences in welfare which are ignored when just monetary income is considered

- The heterogeneity that exists in all facets of the economy points towards the importance of conducting spatial analysis. Assuming space is homogenous can lead to inaccurate outcomes.

- Highlighted the vulnerability of lower income groups to disruptions from extreme weather events.

9.7 Next steps

This analysis was carried out to take a snapshot of the year 2011. Given that the objective of this research was to highlight the sensitivity of the spatial distribution of welfare to definitional changes, the data used was acceptable for this purpose. However given the recent release of the SAPS for Census 2016, there is a requirement to update and produce estimated incomes using the SMILE data for the 2016 data. The methodology framework outlined in this thesis can also be updated using more recent data. The possibility of using the new RPPI index to estimate houses prices at the ED level will be explored.

One of the limitations of the commuting analysis conducted in this thesis was the lack of a congestion measure. This may not be applicable to rural areas however congestion in urban areas leads to large inefficiencies. Spatial methods and the creation of simulated congestion models may be created using GIS software. POWSCAR data will be used for this purpose to attempt in measuring the volume of traffic using a particular road segment. Including congestion produces a more accurate measure of time costs.

One of the major findings was the contrast between the spatial distribution of welfare using income as a proxy and then using life-satisfaction as a proxy. The differences highlight people are willing to forgo extra income for a better quality of life. However, for some reason still unknown they have remained in these areas despite the reported low levels of welfare. More research is required at a small spatial scale on the level of employment opportunities that exist in areas based on a person's level of skills. This also has implications for rural development given the low level of opportunity in vulnerable areas.

Provision of services has a significant impact on individual and household quality of life. These services such as education, medical, public housing and sports facilities however are often poorly measured (Stiglitz et al., 2009b). Increasing availability of geocoded service data through OpenStreetMap and OSi Prime2 makes the study of these drivers of welfare possible.

Using the commuting data created in this thesis it is possible to create new functional geographic areas based on commuter zones as opposed to geographical boundaries. This will allow for comparisons to be made between commuter zones of major cities and towns and other rural areas.

With two of the papers from this thesis already published and another submitted for publication a plan has been created around where to submit the other chapters from this thesis. Given the link between the six papers they could easily be included in a book examining the spatial distribution of welfare in Ireland.

9.8 Dissemination

Publications

Peer Reviewed Publications

Published:

Paul Kilgarriff, Cathal O’Donoghue, Martin Charlton, Ronan Foley (2016). “Intertemporal Income in Ireland (1996-2011) – A Spatial Analysis". International Journal of Microsimulation (IJM).

Amaya Vega, Paul Kilgarriff, Cathal O'Donoghue, Karyn Morrissey (2016). "The Spatial Impact of Commuting on Employment Income - A Spatial Microsimulation Approach" - Applied Spatial Analysis and Policy, Springer.

Conferences attended

May 2017 - Irish Economics Association Annual Conference, Institute of Banking, IFSC, Dublin

Feb. 2017 - Ireland 2040: National Planning Framework Discussion, UCC, Cork

Oct. 2016 - RSA Student and Early Career Conference, Northumbria University, Newcastle

Oct. 2016 – CSO: The Housing Statistics Seminar, Bedford Hall, Dublin Castle

Sept. 2016 - RSA Irish Branch Conference, NUI Galway

May 2016 - Irish Economics Association Annual Conference, NUI Galway

Oct. 2015 - European Association of Agricultural Economists, Edinburgh, Scotland

Sept. 2015 - International Meeting of the International Microsimulation Association, Esch-sur-Azette, Luxembourg

Oct. 2014 - European Meeting of the International Microsimulation Association, Maastricht, Netherlands

Sept. 2014 – Rural Development Conference, Teagasc, Ashtown

Sept. 2014 – Department of Social Protection Workshop, Geary Institute, UCD

List presentations

May 5th 2017 - Irish Economics Association Annual Conference, Institute of Banking, IFSC, Dublin. Title: “Counting the cost of last winter’s flooding: Evidence from disruptions to the road network”.

Oct 28th 2016 - RSA Student and Early Career Conference, Northumbria University, Newcastle. Title: “Effect of a Flood Event on the Daily Commute”

Oct 27th 2016 - RSA Student and Early Career Conference, Northumbria University, Newcastle. Title: “Effect of Housing on the Spatial Distribution of Welfare – A local level imputed rent measure for Ireland”

Sept. 9th 2016 – RSA Irish Branch Conference, NUI Galway. Title: “Census 2016: 2016 Local Area Projections”

May 6th, 2016 – Irish Economics Association Annual Conference, NUI Galway. Title: “The Spatial Impact of Commuting on Employment Income”.

Feb. 3rd, 2016 – Brown Bag Seminar, Department of Economics, NUI Galway. Title: “The Spatial Impact of Commuting on Employment Income” - presented on the effect of travel costs on personal income.

Oct 23rd, 2015 - European Association of Agricultural Economists, Edinburgh, Scotland. Title: “Farm Viability: A Spatial Analysis”.

Sept. 4th, 2015 – International Meeting of the International Microsimulation Association, Esch-sur-Azette, Luxembourg. Title: “Effect of Housing on the Spatial Distribution of Disposable Income”.

Oct 23rd, 2014 - European Meeting of the International Microsimulation Association, Maastricht, Netherlands. Title: “Quantifying the Impact of Space on the Distribution of Welfare”.

Courses attended

Geocomputation NCG602A (Maynooth University)

Spatial Data & GIS GY811 (Maynooth University)

Advanced Microeconomics EC660 (NUI Galway)

Advanced Econometrics EC374 (NUI Galway)

Philosophy of Social Science EC556 (NUI Galway)

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