Social Inclusion:
Does it matter where young people live?

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Abstract

Are young people living in certain urban or rural settings more likely to experience barriers to social inclusion, and if so, what are the nature of the barriers that they face? Using a unique administrative dataset for Ireland's dominant social inclusion programme, this paper examines the effect of location on the incidence of barriers to social inclusion. The five barriers to inclusion examined in this paper are: belonging to a jobless household; being a lone parent; being homeless or affected by housing exclusion; having a disability; and being of an ethnic minority. Our results highlight that urban disadvantage, measured as those experiencing these barriers to social inclusion, is not confined to inner city areas, or the most urban areas, but rather social barriers are more prevalent for young people (aged 18-29) in '*independent urban towns*' all other things being equal. Individuals in such peripheral urban town settings are found to have significantly worse economic outcomes. The results suggest that existing policy, which has traditionally focused on tackling youth social disadvantage in the most urban areas, is not well targeted and would benefit from having a wider spatial focus. Such questions and findings provide evidence that suggest that key differences in the characteristics of individuals facing particular barriers should be reflected in the design and delivery of interventions (education, training, transport, childcare supports) aimed at reducing the impacts of particular forms of social exclusion.

Keywords: Social Inclusion; Community Economic Development; Jobless Household; Lone Parents; Disability; Homelessness; Ethnicity, Young People.

JEL: J02; J08; J68.

1. Introduction

The barriers to social inclusion are multifaceted, complex, and defining the concepts are also challenging. In spite of this, resolving barriers to social inclusion is a continuous focus of both national governments and international bodies. This is in large part due to the interconnected relationships of social exclusion, unemployment and poverty (Atkinson & Hills, 1998). Being marginalized in society not only has a detrimental impact on the individuals affected but also affects societal cohesion more widely.

In terms of potential barriers to social inclusion, jobless households face economic exclusion and are at a greater risk of experiencing poverty; lone parents may face barriers to full economic or social participation; housing distress is a crippling factor faced by many individuals and which also creates a significant barrier to full-economic participation as well as wider civic participation. Policy also tends to focus on combating the social exclusion experienced by groups at higher risk of discrimination, such as persons with disabilities and those belonging to ethnic minorities.

In many instances, policies designed to combat barriers to social inclusion do not tend to discriminate in terms of spatial environment. Furthermore, where policies do have a spatial focus, such as urban or rural policies, the issues addressed tend to be wide-ranging without a heavily targeted focus. A potential explanation for the absence of spatial variations in policy approaches is a lack of data and understanding of the ways in which social exclusion may vary according to area-level characteristics. This paper contributes to the literature, and the wider policy debate, by using a unique dataset to understand how barriers to social inclusion vary by levels of urbanisation in Ireland.

While numerous barriers to social inclusion exist, this paper examines five areas that have been identified as important for youth cohorts within the international literature, for which data exists in Ireland. The barriers to social inclusion considered are: (i) belonging to a jobless household; (ii) being a lone parent; (iii) being homeless or affected by housing exclusion; (iv) having a disability; and (v) belonging to an ethnic minority. The study examines the incidence of the barriers (and combinations of these barriers) faced by young people and their determinants, paying particular attention to the role of spatial factors using the level of urbanisation for neighbourhood small areas. Rather than using an urban-rural binary, this study utilises a six-way classification of the urban-rural continuum: cities; satellite urban towns; independent urban towns, rural areas with high urban influence; rural areas with moderate urban influence; and highly rural/remote areas. Using the urban/rural dichotomy, we find that whether a young person lived in a rural or an urban location had a strong influence on their probability of reporting barriers to social inclusion, with those in urban areas much more likely to face the barriers or combination of barriers examined. However, by utilising the more detailed six-way classification of urban and rural locations, our results highlight that when the barriers to social inclusion relate to economic participation (i.e. being from a jobless household) they are not confined to inner city, or the most urban areas. Our results show that individuals located in '*independent urban towns*' are significantly more likely to report these types of social exclusion, compared to those in cities, satellite towns and rural locations. For other barriers without such an economic component, this does not hold, and these are more likely to be experienced in the most urban areas as per the findings when the dichotomy is used. The research highlights the challenge arising from using the common binary urban/rural indicators and argues that policy design in the areas of both economic deprivation and social inclusion requires a greater sensitivity to level of urbanisation using a more detailed scale.

In summary, this study examines the incidence of barriers to social inclusion, and their determinants, paying particular attention to the role of spatial factors using a six-way urban-rural classification for neighbourhood areas. The research aims to provide clear insights into how policy might be designed to best suit the needs of young people experiencing such barriers, or common combinations of barriers, to inclusion. In any society, ensuring that all young people have the opportunity and support to prosper, both economically and socially, is a priority for government. However, in order to succeed in meeting this challenge it is necessary to understand further the nature of the main barriers that young people face to economic and social inclusion.

2. Literature

Social inclusion/exclusion are multi-faceted and complex concepts but generally one is socially included if they are able to fully participate socially, politically and economically in the society in which they live. A whole range of people/groups can be socially excluded but the most recent EU strategy implemented to deal with social exclusion targeted people with disabilities, younger and older workers, low-skilled workers, migrants and ethnic minorities, those who live in areas of deprivation, and women active in the labour market.

There is a relatively well-developed literature on the incidence, potential determinants, and consequences of each of the barriers to social inclusion considered in this paper. With respect to jobless households at least half of those living in jobless households in most EU countries are either income poor or materially deprived (de Graaf-Zijl and Nolan, 2011). Evidence from Ireland finds that those in jobless households are just over half as likely to subsequently enter employment as an individual from a working household (Watson et al., 2016). Headey and Verick (2006), using Australian data, found that people who lived in jobless households at age 14 were more likely to be welfare dependent and in poverty later in life.

Homelessness and housing distress is now, unfortunately, a consistent feature of almost all modern societies and the barriers to inclusion faced by homeless persons are well documented and researched internationally. Homeless individuals find it difficult to feel part of their community and are also likely to experience many forms of prejudice (Phelan et al., 1997). Those who do not have a permanent address face economic exclusion as they struggle to find employment, as employers are reluctant to hire individuals with no fixed address. In addition, there can be difficulties associated with basic banking and the ability to obtain credit and, therefore, individuals may be forced into accessing black market finance and spiralling debt. The level of homelessness in Ireland has been increasing substantially over very short periods. In January 2017 there were 1,172 homeless families in Ireland, with that figure rising to 1,530 by November 2017. In addition to homelessness, many individuals within society also face some degree of housing distress; for example, Focus Ireland (2016) reported that almost one-third of individuals in Ireland worry about and/or struggle to pay their rent each month.

Lone parents consistently rank as the group most vulnerable to poverty and social exclusion in Ireland and elsewhere (Watson et al., 2016). In 2016, only 56.4 per cent of Irish lone parents were in employment compared to 74.4 per cent of two-parent households (CSO, 2017). Low education levels mean that the jobs available to lone parents often do not pay enough to justify forgoing welfare payments. Consistent with this hypothesis, Zagel (2014), using German and British data, finds that lone parents with at least tertiary education are much more likely to be employed than their lower educated counterparts. This poverty trap is made substantially worse in Ireland when combined with relatively high childcare costs.

Across the EU-28 almost 40 per cent of individuals with a disability confront the risk of poverty or social exclusion (EIGE, 2016), while for Ireland this figure is almost 50 per cent (Watson et al., 2016). Again, this is due to barriers to full economic participation. Individuals with a disability are only about half as likely to be in employment as those who do not have a disability (Watson and Nolan, 2011). Over one-third of individuals in Ireland with a disability who were not employed indicated that they would like to work if the conditions were right

(CSO, 2012). Furthermore, many individuals with a disability may not actively search for employment, for a variety of reasons including fear of losing welfare payments, lack of knowledge of suitable jobs, and/or employer discrimination (CSO, 2007b). Individuals living with disabilities may also face direct monetary costs in terms of paying for disability-related goods and services and thus reducing disposable income and living standards.

Finally, the barriers to inclusion faced by people from ethnic minorities are also well documented. Those from a minority ethnic or cultural background in Ireland, such as Travellers, Roma, refugees, or asylum seekers, are known to face distinct barriers to social and economic integration. Asylum seekers and refugees are particularly vulnerable to social exclusion due to both the traumatic and psychological distress endured in their lifetime and poorer health. Almost half of refugees and asylum seekers coming to the EU are between the ages of 18 and 34, while 25 per cent are children (Benifei, 2016). In addition, non-documented or illegal ethnic minorities are particularly vulnerable to labour exploitation. Their precarious resident status may lead them to accept low pay, long hours, and poor working conditions (Arnold et al., 2017).

While we know the extent of social exclusion among particular groups, and the factors underlying this, little is understood about the degree to which the incidence of social exclusion experienced by individuals is exacerbated by their geographical location and particularly for young people. The literature that does exist tends to focus on deprivation within either strictly urban or strictly rural areas. Drudy and Punch (1999) examines the problem of urban disadvantage in Ireland focusing on the Dublin Region, finding that a substantial portion of the population has been largely excluded from the benefits of economic and social progress which the rest of the population has benefited from in more recent years. Key factors explaining this exclusion relate to high levels of unemployment, educational disadvantage, lone-parent households, as well as the high proportion of people in the unskilled or semi-skilled social classes in urban regions. Langlois and Kitchen (2001) construct twenty indicators of urban deprivation from the Canadian census and using principal component analysis identify the main types of deprivation in the cities and further measure its intensity. This study identifies six main types of urban deprivation (demographic, income, education, language, housing, and employment). Moreover, it is found that urban deprivation in not confined to the inner city, as several of the most severely deprived neighbourhoods are located outside the central city and even in the off-Island suburbs.

Cartmel and Furlong (2000) examine youth employment in rural areas in Scotland focusing on four distinct types of rural areas: a traditional rural area, an urban fringe, a seasonal area and an ex-industrial rural area. They find that the main differences between the areas relate to the level of job opportunities, the availability of seasonal employment and the extent to which poor transport and housing provision inhibits employment possibilities. Furthermore, they find that females in rural areas with children also face more severe disadvantage than their urban counterparts given the lack of childcare facilities.

There is some debate around the extent to which the general urban/rural dichotomy is sufficient for the study of deprivation and social exclusion. Langlois and Kitchen (2001) found severe deprivation not to be concentrated within the most urban areas therefore suggesting the need for a more flexible definition of urbanicity. Harris and Longley (2002) claim that conventional measures of urban deprivation fail to adequately detect within and between small area variations in socioeconomic and environmental conditions. They conclude that adequate representation of diversity requires a greater sensitivity to differentiation at finer scales. Finally, the Cartmel and Furlong (2000) analysis demonstrates the advantage of using the more detailed four-way definition of urbanisation in the context of the study of youth unemployment.

Our research aims to facilitate a more advanced understanding of the process of social inclusion for youth cohorts and how that relates to place of residence in Ireland. A range of research, including quantitative and qualitive work, show that an increasing minority of youths, as a result of changing youth transitions patterns (Johnston et al., 2000, Barry 2001), are at risk of being unable to fulfil their aspirations i.e. obtaining a job, a home, a family, and economic security. Young people who lack qualifications and skills, often have difficulties in establishing themselves in the labour market and can become vulnerable to repeated and extended periods of unemployment. Additional factors linked to vulnerability and social exclusion include a paternal history of unemployment and residence in disadvantaged neighbourhoods (Furlong et al, 2003). Family knowledge and connections are often core to the effective management of transitions for youth.

In the United States, the evidence shows that economic segregation has a driving force of its own. The accumulating negative effects of concentrated poverty can cause households (with the means) to move from these areas, accentuating the concentration of poverty and making it harder for those left behind to get ahead. This creates a vicious cycle of sprawl and economic segregation that has a knock-on effect for society as a whole (Sellers, 1999).

In Europe, historically, poor regions have fewer working poor and more unemployed, but reliance on government welfare (unemployment benefit, health, education, childcare and retirement policies) make the quality of life less dependent on earnings. In theory, such policies reduce inequalities and reduce resistance to economic integration (Musterd and Ostendorf, 2013; Fainstein, 1997).

However, social inequality and residential segregation are increasing in some European countries and cities (Piketty 2014; Tammaru et al., 2016). Although segregation per se need not necessarily be a problem (see for instance Merry, 2016), it can lead to a range of social problems. High levels of segregation may affect the opportunities people have in life and this may lead to a ‘vicious circle of segregation’ for low-income individuals, that often operates over generations (Tammaru et al., 2017).

Nieuwenhuis et al. (2020) study the extent to which people move between different types of neighbourhoods by socio-economic status in different inequality and segregation contexts in four European countries: Sweden, the Netherlands, the UK (England and Wales), and Estonia. For England and Wales, which has long had high levels of income inequalities and high levels of socio-economic segregation, levels of mobility between neighbourhood types are found to be low and opportunities to move to more socio-economically advantaged neighbourhoods are modest. In the Netherlands and Sweden, where income inequalities are the smallest, they find that it is easiest to move from the most deprived to less deprived neighbourhoods. Their overall conclusion is that the combination of high levels of income inequalities and high levels of spatial segregation tend to lead to a vicious circle of segregation for low-income groups, where it is difficult to undertake upward socio-spatial mobility.

3. Data and Methodology

Data for the study comes from the 2016 monitoring database for Ireland's Social Inclusion and Community Action Plan (SICAP). SICAP aims to tackle poverty, social exclusion and inequality through local engagement and partnerships between disadvantaged individuals, community organisations and public sector agencies. It is the dominant initiative of its kind in Ireland. The programme is funded and overseen by the Department of Rural and Community Development (DRCD)[1] and Pobal. It is co-funded by the European Social Fund (ESF), including a special allocation under the Youth Employment Initiative (YEI) and received a total programme budget of €35.8 million in 2016. The Integrated Reporting and Information System (IRIS) is an administrative data capture system that is used by SICAP Programme Implementers (PIs) when registering individuals for SICAP supports. IRIS contains information about individuals, such as age, gender, education, and economic status of all SICAP participants. Information on barriers to the specific barriers to social inclusion listed earlier are also captured. Crucially, the data also contains a small area code related to each person's home address, which allowed us to match the data on individuals with the Central Statistical Office (CSO) six-way geographical classification.

[1] The responsibility for SICAP was previously with the Department of Housing, Planning and Local Government (DHPCLG) but was moved in June 2017 to the Department of Rural and Community Development (DRCD).

IRIS is a national database which includes individuals who are likely to seek supports in the areas of programmes and projects aimed at either: (i) enhancing social inclusion, (ii) providing life-long learning, or (iii) delivering employment supports with a particular focus on disadvantaged job seekers. As SICAP is Ireland's major policy body responsible for programmes designed to address social exclusion, the data provides an accurate national picture of the prevalence of various forms of social exclusion and how these are distributed nationally. The data will therefore not be representative of the population. The dataset also contains information on a subset of individuals reporting no forms of exclusion, such as those who access SICAP for lifelong learning supports, thus providing us with a natural reference category for our study. As SICAP funding is area based, the dataset is ideal for examining the role of area-based characteristics on social exclusion risk and is quite unique from a research perspective. With respect to the sample, we begin with a complete sample of 46,259 individuals who accessed SICAP supports in 2016 before excluding 1,256 who could not be matched to an urban/rural category, as they had provided no details of their geographical location. Following this exclusion, we selected only those aged between 18 and 29 given our interest in the youth cohort which reduces our operational sample to 9,766 observations.

Our estimation strategy is described as follows; we begin by estimating Equation 1:

$$Ex^{*} = \alpha + \beta_1 X_i + \beta_2 T_i + \varepsilon_i \qquad (1)$$

Ex^{*} is a latent variable measuring the probability that a young individual *'i'* will experience a particular form of social exclusion; X_i is a set of explanatory variables for individual *i* (age, education, gender, nationality, live register status); T_i is a set of dummy variables that measure urbanisation while α and ε are the constant and error terms, respectively. In each model, the sample will compare all individuals reporting the form of social exclusion against a reference group of individuals who report experiencing no forms of social exclusion. This approach ensures that each sub-group reporting a particular form of social exclusion will be compared with a constant reference group, thus ensuring that the results from the individual models are directly comparable.

However, we must be conscious of the possibility that the location variable may be correlated with other controls in the model, such as, age, gender, nationality, or live register status, which may also determine the probability of experiencing a particular form of social exclusion. If this occurs, then the estimates of our urbanisation coefficients will be confounded with other variables in the model, leading to potentially biased estimates. To overcome this issue, we also estimate the impacts of urbanisation of social exclusion using Propensity Score Matching (PSM) techniques. The propensity score is defined as the conditional probability of receiving a treatment given certain determining characteristics (Equation 2):

$$p(X) = Pr\{D = 1/X\} = E\{D/X\} \quad (2)$$

D indicates exposure to the treatment (social exclusion), and X is a vector of determining characteristics.

In the second stage of the PSM estimation procedure, youths in the treatment group (experiencing a form of social exclusion) are “matched” with counterparts in the control group (reporting no forms of social exclusion) that have similar propensity scores of being subject to the treatment effect and their actual outcomes are compared. Rosenbaum and Ruben (1983) show that matching individuals based on propensity scores is equivalent to matching on actual characteristics. This ensures that any distortions related to selection bias are eradicated. It should be noted that, as in the case of Equation 1, a constant control group of individuals, reporting no forms of social exclusion, are used for all the PSM estimates thus allowing for direct comparability.

The main limitations of the PSM approach are: (i) it may not be possible to eradicate all observable differences between the control and treatment groups post matching, and (ii) matching helps control only for observable differences and not unobservable differences; thus, unobserved heterogeneity remains a problem. To address the former, we undertake several post-estimation tests to ensure that the control and treatment groups are balanced on all covariates relevant to assignment to the treatment. To address the latter, that the PSM approach does not solve for potential selection on unobservables, the reliability of any propensity score matching estimate is dependent upon the Conditional Independence Assumption (CIA) being met. This assumption implies that selection to the treatment is based solely on observables within the dataset, and where all variables that simultaneously impact both the treatment and outcome variable are also observed. By any conventional standards we would be confident that the additional SICAP information contained within our dataset would capture most of the relevant factors.

We nevertheless conduct further sensitivity tests that gives us a sense to which our matching estimates are prone to the presence on unobserved heterogeneity (Becker and Caliendo, 2007). These procedures, which are conducted using the *MHbounds* procedure, in the Stata statistical software package, essentially introduce an unobserved factor that simultaneously increases the likelihood of allocation to the treatment group and the outcome variable. Specifically, the methodology examines the impact of unobservables that increase the odds of allocation to the treatment and are simultaneously associated with higher (termed positive selection bias) or lower (termed negative selection bias) levels of the outcome variable. Effectively, the sensitivity test measures the extent to which an unobserved factor must influence the odds of being allocated to the treatment group, under the assumptions of either positive or negative selection bias, before the estimated treatment effect becomes statistically unreliable. The test does not demonstrate bias per se but gives us a sense of how the statistical significance of our estimates may be sensitive to the presence of unobserved influences.

4. Results

Table 1 provides some broad descriptives of the sample. As expected, given the objectives of SICAP individuals, lower-level qualifications are over-represented relative to the national average, with persons qualified to National Framework Qualifications (NFQ) 1,2 and 3 (Junior Certificate or below) accounting for 28% of the sample. Persons educated to NFQ 4 and 5 (Leaving Certificate) level account for about half the sample (53%).

Table 1: Sample Characteristics

Variable	Total
Urban/Rural	
Urban	73%
Rural	27%
Gender	
Male	57%
Female	43%
Age	
18 - 24 years	63%
25 - 29 years	37%
Education	
NFQ <4	28%
NFQ 4 & 5	53%
NFQ 6 & 7 & 8	18%
NFQ 9 & 10	1%
Nationality	
Irish	87%
EU New	5%
EU Old	4%
Non-EU	4%
Live Register	
Less than 6 months	13%
6-12 months	12%
13-24 months	14%
More than 24 months	20%
N	**9,766**

A large proportion of the youth cohort are towards the younger end of the scale, the average age is 23 years, and males account for a larger share of SICAP participants than females. Persons born outside of Ireland account for 13 per cent of the population, which is broadly in line with the population average. Finally, with respect to urbanisation, 73% (27%) of the sample are classified as living in urban (rural) using the standard dichotomy.

However, as discussed above, the standard binary urban/rural classification is likely to mask substantial heterogeneity with respect to social exclusion and we instead employ a more detailed six-way classification. This six-way classification is a relatively new addition within Irish data. The six-way classification is based on the population of small areas and a measure of the flows of people to cities for work.[2] The classification is broken into three urban area types: cities, satellite urban towns, and independent urban towns with the population share located in each standing at 36 per cent, 9 per cent and 25 per cent, respectively. Three rural area types are also included in the six-way classification: rural areas with a high urban influence, rural areas with a moderate urban influence and highly rural/remote areas with associated population shares of 9 per cent, 10 per cent and 12 per cent, respectively.

Table 2 provides a detailed description of the classifications and information on the population share of each spatial category both within our data (Column 6) and also at a population level (Column 5). The youth sample is somewhat over-representative of '*independent urban towns*' which, given the nature of SICAP, suggests a disproportionately higher incidence of barriers to social inclusion in these areas. Conversely '*rural areas with high urban influence*' and '*satellite urban towns*' have a somewhat lower share of these barriers relative to the national youth population.

[2] For more info on the six-way classification see https://www.cso.ie/en/releasesandpublications/ep/p-urli/urbanandrurallifeinireland2019/introduction/

Table 2: Six-Way Classification - Prevalence in the Youth Population and Sample

		Type	Definition	Population (15-64 years)	Youth sample
Urban areas	1	**Cities**	Towns/settlements with populations greater than 50,000 - using Census 2016 definitions/breakdowns.	35%	38%
	2	**Satellite Urban Towns**	Towns/settlements with populations between 1,500 and 49,999, where 20 percent or more of the usually resident employed population's workplace address is in 'Cities'.	13%	6%
	3	**Independent urban towns**	Towns/settlements with populations between 1,500 and 49,999, where less than 20 percent of the usually resident employed population's workplace address is in 'Cities'.	16%	29%
Rural Areas	4	**Rural areas with high urban influence**	Rural areas (themselves defined as having an area type with a population less than 1,500 persons, as per Census 2016) are allocated to one of three sub-categories, based on their dependence on urban areas. Again, employment location is the defining variable. The allocation is based on a weighted percentage of resident employed adults of a rural Small Area who work in the three standard categories of urban area (for simplicity the methodology uses main, secondary, and minor urban area). The percentages working in each urban area were weighted using multipliers. The multipliers allowed for the increasing urbanisation for different sized urban areas. For example, the percentage of rural people working in a main urban area had double the impact of the same percentage working in a minor urban area. The weighting acknowledges the impact that a large urban centre has on its surrounding area. The adopted weights for: Main Urban areas is 2, Satellite urban communities is 1.5, Independent urban communities is 1. The weighted percentages is divided into tertials to assign one of the three rural breakdowns	16%	7%
	5	**Rural areas with moderate urban influence**	As above	12%	9%
	6	**Highly rural/remote areas**	As above	8%	10%
		All		**3,061,508**	**9,766**

Table 3 shows the prevalence of the barriers to social inclusion (and the combinations of barriers) which were most prevalent in the youth sample and the prevalence by area type. The first thing to note is that 48.3 per cent of youths reported no barriers to social exclusion, with such individuals likely to be receiving life-long learning supports through SICAP; this group represents the comparison group for all our models and the large sample size ensures that our matching estimates are likely to be robust.

Focusing only on those individuals reporting particular barriers to inclusion, we can see that a few categories dominate. Young people from jobless households account for approximately 28 per cent of the total sample (56 per cent of those reporting barriers), young people from jobless households who are also lone parents make up 4 per cent of the total sample (8 per cent of those reporting barriers). Other groups of significance are lone parents and persons with disabilities that account for 7 per cent of the total sample (and 14 per cent of those reporting barriers). Five category combinations account for almost two-thirds of all those reporting barriers to inclusion.

Some significant differences can be seen with respect to the interaction between barriers to exclusion and the spatial variables, most noticeably, just 42 per cent of individuals in '*independent rural towns*' report no barriers to inclusion compared the national average of 50 per cent; these areas were particularly over-represented among those with jobless households and ethnic minorities. Conversely, the incidence of individuals reporting barriers to inclusion was lower in highly rural/remote areas compared to the national average.

Table 3: Prevalence of Barriers to Social Inclusion by Area Type

	Barriers reported	Freq	%	Cities	Satellite urban towns	Independent urban towns	Rural areas - high urban influence	Rural areas - moderate urban influence	Highly rural/remote areas
1	None	4,911	50%	54%	52%	42%	57%	52%	52%
2	Jobless household	2,722	28%	25%	27%	33%	24%	27%	29%
3	Person with a disability	376	4%	3%	5%	3%	6%	7%	7%
4	Jobless household and lone parent	372	4%	4%	3%	4%	2%	4%	3%
5	Jobless household and ethnic minority	285	3%	2%	2%	6%	1%	2%	2%
6	Lone parent	273	3%	4%	2%	2%	2%	2%	2%
7	Jobless household and person with a disability	185	2%	1%	2%	3%	2%	2%	3%
8	Ethnic minority	154	2%	2%	1%	2%	1%	1%	1%
9	Jobless household and homeless or affected by housing exclusion	148	2%	2%	2%	2%	1%	1%	1%
10	Homeless of affected by housing exclusion	111	1%	2%	1%	1%	1%	0%	0%
11	Other combinations	229	2%	3%	3%	3%	2%	1%	1%
	Number of observations	9,766		3,670	620	2,825	727	910	1,014

Table 4 presents the results from a series of probit models based on Equation 1, the outcome measure is a binary variable capturing the presence of the main categories of social exclusion discussed above. In each model, the sample consists of youth SICAP respondents experiencing the specific barrier to social inclusion and those reporting no barriers to social inclusion, hence the sample size varies across models. In addition to our measures of urbanisation, each model also controls for gender, age, nationality, education, live register history, and the area-level deprivation. The control variables included in each model vary to account for potential collinearity. The fact that we are controlling for small-area deprivation ensures that any impact observed in the model is over and above those explained by general levels of deprivation in the six urban/rural categories.

The first row in the model reports the results where we include a single urban binary variable along with the specified set of control variables. Relative to areas classified as rural, we can see that youths located in urban areas are much more likely to experience all forms of social exclusion, except jobless household, and jobless household and person with disability, with the estimated marginal effects highest for youths with disability (4 percentage points). Individuals in urban areas are approximately 2 percentage points more likely to report each of the other forms of social exclusion than those in rural areas.

We proceed by replacing the single urban binary variable with the new six-way classification measure using the most rural (‘*highly rural/remote’*) category as a reference category (results also shown in Table 4). We observe substantial variation in the impact of the spatial variables, with the probability of all barriers to social inclusion higher among individuals in areas other than the reference category (except disability where the effects are negative) and the marginal effects particularly high for individuals from jobless households. The risk of social exclusion is higher for people living in urban areas but more specifically for those in areas classified as ‘*independent urban towns*’. Persons from ‘*independent urban towns*’ are 8 (3) percentage points more likely to report as being from a jobless household (being from a jobless household and a lone parent) than those from the most rural/remote areas.[3] The respective findings for individuals from ‘*cities’* are not statistically significant from the reference category. In fact, the prevalence of barriers to social inclusion was highest among individuals located in ‘*independent urban towns*’ in five of the nine categories measured in the dataset. Four of these are related to economic participation – being from a jobless household; being from a jobless household and a lone parent; being from a jobless household and being from an ethnic minority; and, being from a jobless household and homeless or affected by housing exclusion.

Persons from ‘*cities*’ also appear to have an elevated exposure to the combination of jobless household and lone parenthood, but not to the same extent as ‘*independent urban towns*’. However, the prevalence to lone parenthood, is most significant in ‘cities’. Persons from

[3] These findings become more pronounced when we consider the entire adult cohort (aged 18-65) where persons from ‘*independent urban towns*’ are 15 (12) percentage points more likely to report as being from a jobless household (being from a jobless household and a lone parent) than those from the most rural/remote areas.

‘*satellite urban towns*’ do not appear to have the same elevated rates as either ‘*independent urban towns*’ or ‘*cities*’. For some categories, namely belonging to an ethnic minority, the combination of jobless household and housing exclusion, lone parenthood, and having a disability, there is no increased risk of being socially excluded amongst any of the rural spatial categories. While for social exclusion in the form of being from a jobless household and lone parent, residing in a ‘*rural area with moderate urban influence’* sees a somewhat elevated probability relative to counterparts in the most rural areas. These results point to the usefulness of this six-way classification over the urban/rural binary given how the results differ considerably from the urban coefficient in the first row.

Table 4: Estimation Results (Marginal Effects) from Probit Models Examining Barriers to Social Inclusion for Youths (aged 18-29) by Location Types

	Jobless household	Person with a disability	Jobless household and lone parent	Jobless household and ethnic minority	Lone parent	Jobless household and person with a disability	Ethnic minority	Jobless household and homeless or affected by housing exclusion	Homeless of affected by housing exclusion
Urban	*0.02 **	*-0.04 ****	*0.01 ***	*0.02 ***	*0.02 ****	*0.00*	*0.02 ****	*0.02 ****	*0.02 ****
Cities	-0.03	-0.05 ***	0.02 **	-0.01	0.04 ***	-0.02 **	0.02 *	0.02 **	0.02 ***
Satellite urban towns	0.03	-0.02	0.02	-0.01	0.03 *	-0.01	0.01	0.03 *	0.02
Independent urban towns	0.08 ***	-0.03 ***	0.03 ***	0.04 ***	0.02	0.01	0.04 ***	0.04 ***	0.01
Rural areas with high urban influence	-0.03	-0.01	0.00	-0.02 *	0.01	-0.01	0.00	0.00	0.00
Rural areas with moderate urban influence	0.01	0.00	0.03 *	0.00	0.01	-0.01	-0.01	-0.01	-0.01
Highly rural/remote areas					Reference Category				
Age, education, gender, deprivation	X	X	X	X	X	X	X	X	X
Nationality	X	X	X		X	X		X	X
Live Register		X			X		X		X
Frequency of barrier/s	2722	376	372	285	273	185	154	148	111
N	6904	4711	4609	5195	4590	4441	4342	4394	4438
Pseudo R2	0.03	0.13	0.19	0.20	0.13	0.07	0.11	0.05	0.06

5. Robustness Analysis

We next re-estimate the impacts using a PSM approach designed to eradicate bias related to non-random sample selection. The samples are the same for each estimate (individuals experiencing the barrier to social inclusion, or combination of barriers, and those reporting no barriers faced) with the treatment categories in each case being one of the spatial categories, for instance, persons from '*cities*'. Our estimates will measure the extent to which persons in a particular spatial category are more likely to experience a particular barrier to social inclusion compared to those located in the reference category of '*highly rural/remote areas*'.[4] The sample construction makes our PSM estimates directly comparable with those from Table 4.

Table 5 contains the PSM estimates alongside those from the previous probit models for ease of comparison. We begin by examining the estimates for the most pronounced impacts, generally the PSM estimates align with those from the probit models in terms of both the levels and significance. Nevertheless, there are a couple of instances where impacts observed within the probit framework are no longer evident under PSM. Most noticeably some of the social exclusion coefficients for '*cities*' and '*satellite towns*', evident within the probit analysis, are statistically insignificant within the PSM framework. In only one instance, did we find a statistically significant result in the PSM that was not evident under the probit models; the PSM analysis generally confirms the results generated by our earlier models.[5] In particular, it

[4] To ensure consistency with the probit models, individuals from the remaining spatial categories are dropped from the sample.
[5] The marginal effects on cities for the jobless household variable, is the only exception.

confirms the main findings in the previous section that barriers to social inclusion are not necessarily more likely in urban areas but are driven by the ‘*independent urban towns*’.

Nevertheless, we must ensure that our PSM data is sufficiently balanced so that we can be confident that the individuals in the various treatment groups experiencing various barriers, were indeed matched with individuals with similar characteristics from the control group, those who experience no barriers to social inclusion. If matching were accurate this would ensure that the only characteristic that would differ between the control and treatment group members was the degree of urbanisation of the area in which they reside. A first indication that matching is successful is when the Pseudo R^2 statistic approaches zero when we re-run an outcome model on the matched sample and as can be seen from Table 5, the post-matching Pseudo R^2 estimates fall to either 0.00 or 0.01 from their pre-matched levels.

More formal balancing test statistics included in Table 5 are the Rubin’s R and the Rubin’s B statistics. The Rubins’ B score is the absolute standardised difference of the means of the linear index of the propensity score in the treated and (matched) non-treated group. The Rubins’ R score is the ratio of the treated to (matched) non-treated variances of the propensity score index. To indicate that the samples are considered sufficiently balanced, it is recommended that the Rubins’ B score is less than 25 and Rubins’ R score lies between 0.5 and 2 (See Rubin 2001 for more details). Without exception, all the balancing tests fall within the required ranges, thus confirming the reliability of our matching estimates.

Our final checks relate to the robustness of our PSM estimates to unobserved factors that may potentially impact assignment to the various treatment groups. We use the MH Bounds procedure in STATA (Becker and Caliendo, 2007) that allows us to introduce an unobserved factor that simultaneously increases the likelihood of facing a form of social exclusion and increases the likelihood of allocation to the treatment group (termed positive selection bias) to assess if our estimated treatment effect remains statistically reliable. Effectively, the sensitivity test measures the extent to which an unobserved factor must influence the odds of being allocated to the treatment group before the estimated treatment effect becomes statistically unreliable.

In terms of acceptable thresholds for the test statistic, an application of the approach to the data from the minimum wage study by Card and Kruger establish that the results of that study would become unreliable with lower values of between 1.34 and 1.5 (Rosenbaum, 2002). Thus, we might think of an MH Bounds statistic over 1.5 as an indication that the estimates are relatively robust to the potential impacts of unobserved heterogeneity. It is important to note that a test statistic of below 1.5 is not an indicator of bias, but simply that the estimate has the potential to be affected by an unobserved biasing factor. The tests are only run on PSM estimates that are statistically significant. We find that of the 12 post estimation tests that were ran (for estimates that were both highly significant in the probit and PSM estimations), all exceeded the acceptable threshold, suggesting that our PSM estimates are likely to be relatively robust to the potential impacts of unobserved heterogeneity. The potentially statistically unreliable results relate to areas with moderate/high rural interest, which is perhaps unsurprising given their similarity to the highly rural reference category.

Table 5: Estimation Results (Marginal Effects) from Probit and Propensity Score Matching (PSM) Examining Barriers to Social Inclusion for Youths (aged 18-29) by Location Types

Jobless household	Probit Coefficient		PSM ATT		Pseudo R2 (Pre)		Pseudo R2 (Post)		B	R	MHBounds
(i) Jobless household											
Cities	-0.03		-0.06	***	0.05	***	0.00	**	11.1	0.9	
Satellite urban towns	0.03		0.01		0.04	***	0.00		9	1.0	
Independent urban towns	0.08	***	0.06	***	0.035	***	0.00		5.7	1.1	1.25
Rural areas with high urban influence	-0.03		-0.02		0.135	***	0.00		6.7	1.1	
Rural areas with moderate urban influence	0.01		0.02		0.07	***	0.00		3.4	1.0	
Highly rural/remote areas	**Reference Case**										
(ii) Person with a disability	**Probit Coefficient**		**PSM ATT**		**Pseudo R2 (Pre)**		**Pseudo R2 (Post)**		**B**	**R**	**MHBounds**
Cities	-0.05	***	-0.07	***	0.02	***	0.00		10.9	1.1	1.7
Satellite urban towns	-0.02		-0.02		0.13	***	0.02	*	39.7	1.0	
Independent urban towns	-0.03	***	-0.03	**	0.03	***	0.00		9.8	1.0	1.5
Rural areas with high urban influence	-0.01		-0.01		0.22	***	0.00		13.4	1.2	
Rural areas with moderate urban influence	0.00		0.01		0.08	***	0.00		6.7	0.9	
Highly rural/remote areas	**Reference Case**										
(iii) Jobless household and lone parent	**Probit Coefficient**		**PSM ATT**		**Pseudo R2 (Pre)**		**Pseudo R2 (Post)**		**B**	**R**	**MHBounds**
Cities	0.02	**	0.02	*	0.05	***	0.00		8.9	1.0	1.3
Satellite urban towns	0.02		-0.01		0.05	***	0.00		13	0.8	
Independent urban towns	0.03	***	0.03	**	0.04	***	0.00		6	0.9	1.35
Rural areas with high urban influence	0.00		0.01		0.13	***	0.00		5.6	1.0	
Rural areas with moderate urban influence	0.03	*	0.04	***	0.06	***	0.00		4.4	1.0	1
Highly rural/remote areas	**Reference Case**										

Propensity Score Matching Results (Cont'd)

(iv) Jobless household and ethnic minority	Probit Coefficient		PSM ATT		Pseudo R2 (Pre)		Pseudo R2 (Post)		B	R	MHBounds
Cities	-0.01		-0.02	**	0.01	***	0.00		5.1	1.6	
Satellite urban towns	-0.01		0.01		0.10	***	0.00		12.7	1.0	
Independent urban towns	0.04	***	0.06	***	0.01	***	0.00		4.1	1.1	2.1
Rural areas with high urban influence	-0.02	*	-0.01		0.22	***	0.00		6.9	0.9	
Rural areas with moderate urban influence	0.00		0.01		0.07	***	0.00		4.4	0.9	
Highly rural/remote areas	**Reference Case**										
(v) Lone Parent	**Probit Coefficient**		**PSM ATT**		**Pseudo R2 (Pre)**		**Pseudo R2 (Post)**		**B**	**R**	**MHBounds**
Cities	0.04	***	0.05	***	0.02	***	0.00		9.5	1.3	1.7
Satellite urban towns	0.03	*	0.03	*	0.12	***	0.01		24.1	1.2	
Independent urban towns	0.02		0.02	*	0.03	***	0.00		9.8	1.1	
Rural areas with high urban influence	0.01		0.01		0.23	***	0.00		12	1.0	
Rural areas with moderate urban influence	0.01		0.00		0.08	***	0.00		9.8	1.0	
Highly rural/remote areas	**Reference Case**										
(vi) Jobless Household and Person with a Disability	**Probit Coefficient**		**PSM ATT**		**Pseudo R2 (Pre)**		**Pseudo R2 (Post)**		**B**	**R**	**MHBounds**
Cities	-0.02	**	-0.02	*	0.06	***	0.00		13.3	0.9	
Satellite urban towns	-0.01		0.02		0.06	***	0.00		9.8	1.0	
Independent urban towns	0.01		0.01		0.04	***	0.00		9.3	1.0	
Rural areas with high urban influence	-0.01		-0.01		0.12	***	0.00		4.9	1.0	
Rural areas with moderate urban influence	-0.01		-0.01		0.06	***	0.00		3.6	1.0	
Highly rural/remote areas	**Reference Case**										

Propensity Score Matching Results (Cont'd)											
(vii) Ethnic Minority	**Probit Coefficient**		**PSM ATT**		**Pseudo R2 (Pre)**		**Pseudo R2 (Post)**		**B**	**R**	**MHBounds**
Cities	0.02	*	0.01	**	0.02	***	0.00		5.9	1.1	
Satellite urban towns	0.01		0.01		0.10	***	0.01		24.5	1.0	
Independent urban towns	0.04	***	0.02	***	0.01	***	0.00		4.1	1.0	1.7
Rural areas with high urban influence	0.00		0.01		0.22	***	0.00		10.7	1.0	
Rural areas with moderate urban influence	-0.01		0.00		0.09	***	0.00		12.6	0.8	
Highly rural/remote areas	**Reference Case**										
(viii) Jobless Household and Homeless or affected by housing exclusion	**Probit Coefficient**		**PSM ATT**		**Pseudo R2 (Pre)**		**Pseudo R2 (Post)**		**B**	**R**	**MHBounds**
Cities	0.02	**	0.02	***	0.05	***	0.00		6.5	0.9	1.4
Satellite urban towns	0.03	*	0.01		0.06	***	0.00		9.2	0.8	
Independent urban towns	0.04	***	0.02	***	0.04	***	0.00		8	1.1	1.5
Rural areas with high urban influence	0.00		0.00		0.12	***	0.00		4.6	0.9	
Rural areas with moderate urban influence	-0.01		-0.010		0.06	***	0.00		3.2	1.0	
Highly rural/remote areas	**Reference Case**										
(ix) Homeless or affected by housing exclusion	**Probit Coefficient**		**PSM ATT**		**Pseudo R2 (Pre)**		**Pseudo R2 (Post)**		**B**	**R**	**MHBounds**
Cities	0.02	***	0.02	***	0.03	***	0.00	***	8.2	1.2	1.7
Satellite urban towns	0.02		0.01		0.13	***	0.01		25.1	1.1	
Independent urban towns	0.01		0.01	*	0.03	***	0.00		9.9	0.9	
Rural areas with high urban influence	0.00		-0.01		0.22	***	0.00		14.0	1.0	
Rural areas with moderate urban influence	-0.01		-0.01	*	0.08	***	0.00		9.3	1.0	
Highly rural/remote areas	**Reference Case**										

6. Conclusions

In this paper, we utilize a novel dataset and a six-way classification of urbanisation to assess the extent to which the risk of various forms of social exclusion are more likely for young people in Ireland. Using this more detailed classification, rather than the generally used urban/rural binary variable, we find evidence of substantial heterogeneity across different areas of urbanisation. This is of specific importance given the reliance on the urban/rural dichotomy for policy making reasons. Other statistics agencies have also developed similar more detailed urban/rural classifications and the findings herein reiterate the importance of a more precise classification of area and the use of same should be encouraged in both research and policymaking in Ireland and internationally.

Using the binary urban/rural variable, we find that young people residing in urban areas are more likely to face particular barriers to social inclusion relative to their peers in rural areas. However, on stricter examination with the more precise six-way classification, the risk of certain types of social exclusion is noticeably higher not for those in the most urban areas but for young people living in '*independent urban towns*'; the marginal effects for living in a jobless household only, and the combination of jobless household and ethnic minority are both six percentage points higher. In fact, the risk of social exclusion was highest among youths located in '*independent urban towns*' in five of the nine social exclusion categories measured in the data (namely, belonging to a jobless household; jobless household and lone parent; jobless household and ethnic minority; ethnic minority; and jobless household and homeless or affected by housing exclusion). That is, economic exclusion is more likely in *'independent urban towns'* than in any other types of areas.

Young people from ‘*cities*’ also appear to have an elevated exposure to being from a jobless household and lone parenthood combined and lone parenthood in isolation, and jobless household and homeless or affected by housing exclusion, compared to rural areas but not to the same extent as is the impact of living in an ‘*independent urban town’*. However, youths residing in ‘*satellite urban towns*’ do not appear to have elevated impacts, across the range of the barriers, compared to youths residing in the rural areas.

There may be several potential explanations for this finding. Firstly, youth policy initiatives tend to be defined as either urban or rural with the focus of programmes and policy-related spending tending to be more concentrated according to aspects of both measures i.e., either within cities or highly rural/remote areas. As a consequence, satellite, and urban towns, that fall somewhere between both definitions, tend to be more neglected from a policy perspective which, in turn, raises the incidence of social exclusion in these areas.

Furthermore, some *‘independent urban towns’* differ from *‘satellite urban towns’* based on the proportion who work in a city and as such may be further from cities and thus further from economic opportunities. On the other hand, some *‘independent urban towns’* are not necessarily further from *‘cities’*; but may not be connected as well as other areas. Our findings showing that rural communities do not suffer to the same extent from social exclusion may reflect the benefits rural policy has in protecting rural residents from social exclusion. However, distance from economic opportunity, services, access to transport and intergenerational contextual mobility are well documented in the literature as impeding social inclusion and may be impacting *‘independent urban towns’* but *not ‘satellite urban* *towns'*. For example, Currie (2009) reviews the links between transport and social disadvantage from an economic perspective in urban Australia, finding that land values and infrastructure pricing policies, or a lack thereof, have acted to encourage sprawl and the location of lower income groups in fringe urban areas.

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