Health & Place 46 (2017) 29–36

Contents lists available at ScienceDirect

Health & Place

journal homepage: www.elsevier.com/locate/healthplace

Improving spatial microsimulation estimates of health outcomes by including geographic indicators of health behaviour: The example of problem gambling

Francis Markham[a,*], Martin Young[b], Bruce Doran[a]

[a] Fenner School of Environment and Society, The Australian National University, 48A Linnaeus Way, Canberra, ACT 2601, Australia
[b] School of Business and Tourism, Southern Cross University, Hogbin Drive, Coffs Harbour, NSW 2450, Australia

ARTICLE INFO

Keywords:
Spatial microsimulation
Model specification
Electronic gaming machines
Problem gambling
Gambling

ABSTRACT

Gambling is an important public health issue, with recent estimates ranking it as the third largest contributor of disability adjusted life years lost to ill-health. However, no studies to date have estimated the spatial distribution of gambling-related harm in small areas on the basis of surveys of problem gambling. This study extends spatial microsimulation approaches to include a spatially-referenced measure of health behaviour as a constraint variable in order to better estimate the spatial distribution of problem gambling. Specifically, this study allocates georeferenced electronic gaming machine expenditure data to small residential areas using a Huff model. This study demonstrates how the incorporation of auxiliary spatial data on health behaviours such as gambling expenditure can improve spatial microsimulation estimates of health outcomes like problem gambling.

1. Introduction

1.1. Background

Problem gambling, characterised by difficulties limiting time and money spent gambling, is a significant and growing public health issue. Harms arising from problem gambling often include financial stress, deteriorated mental and physical health, strained interpersonal relationships, violence and crime. The serious nature of these impacts, combined with their relatively high prevalence in the population, means that problem gambling is, in aggregate, a serious public health burden. For example, problem gambling has been estimated to be the third-largest contributor to the burden of disability in Victoria, Australia, following major depression and alcohol abuse and dependence (Browne et al., 2016).

Despite its significance as a public health problem, little is currently known about the spatial distribution of problem gambling. Unpublished administrative data on gambling expenditure tends to show highly uneven spatial distributions, suggestive of gambling-related health inequalities. Yet few scholars have specifically examined the spatial distribution of gambling losses. One notable exception is a study by Rintoul et al. (2013), which found that per capita electronic gaming machine (EGM) expenditure was highly concentrated in the most disadvantaged areas of Melbourne. More frequently, the spatial distribution of gambling venues has been mapped and correlated with indicators of deprivation or socioeconomic disadvantage. For example, studies of betting shops in London in 1966 (Newman, 1972) and 2010 (Wardle et al., 2014) show that a historical spatial concentration in more deprived neighbours continues to contemporary times. Similar spatial relationships between EGM venue density and disadvantage have been consistently observed in Australia, Canada, and New Zealand (e.g. Marshall and Baker, 2002; Rush et al., 2007; Wheeler et al., 2006). Moreover, the relationship between venue density and disadvantage may be robust to changes in scale, with modest spatial correlations evident for small geographic zones (with an average of 225 dwellings), as well as for much larger spatial units with populations measured in the tens of thousands (Marshall and Baker, 2001).

The uneven provisioning of gambling venues and gambling expenditure suggests that the prevalence of problem gambling is also likely to be spatially patterned. Yet the degree to which the health burden of problem gambling is spatially uneven is currently unknown. Put simply, it is unclear if residents of some areas suffer from the adverse impacts of gambling more than others.

A spatial approach to modelling the prevalence of problem gambling is required in order to understand these geographic health inequalities. Beyond an academic imperative to understand the distribution of gambling harms, knowledge of the location of areas of high and low problem gambling prevalence would be useful for a range of

* Corresponding author.
E-mail addresses: francis.markham@anu.edu.au (F. Markham), martin.young@scu.edu.au (M. Young), bruce.doran@anu.edu.au (B. Doran).

http://dx.doi.org/10.1016/j.healthplace.2017.04.008
Received 2 January 2017; Received in revised form 24 April 2017; Accepted 24 April 2017
Available online 29 April 2017
1353-8292/© 2017 Elsevier Ltd. All rights reserved.

practical applications. For example, licensing authorities are typically required to undertake local social impact assessments when new gambling venues are proposed, a task which is difficult to undertake in the absence of local data on the prevalence of problem gambling. Similarly, resources for treatment services ought to be provisioned on the basis of local needs. In short, there are both academic and practical imperatives to understand the spatial distribution of problem gambling.

Yet no studies to date have explicitly sought to estimate the prevalence of problem gambling in small areas. Five notable studies have, however, sought to map the distribution of what Welsh *et al.* term 'debtogenic landscapes' (Welsh et al., 2014) - urban environments conducive to, or symptomatic of, problem gambling. Taking a combinatory approach, Robitaille and Herjean (2008) mapped the demographic risk factors for problem gambling (i.e. gender, age, income, marital status, income, ethnicity and employment status) and found a spatial correlation between areas of high-risk demographics and the accessibility of gambling venues. Doran and Young (2010) undertook a conceptually similar study, but used index modelling and substituted an index of disadvantage derived using principle components analysis in place of Robitaille and Herjean's separate risk factor layers. This methodology that has since been replicated (Conway, 2015). Rintoul et al. (2013) extended this approach, weighting accessibility scores for venues by the volume of EGM expenditure within those venues, rather than following Doran and Young's approach of weighting venues by number of EGMs. The most comprehensive study to date has been that of Wardle et al. (2016). This study produced a weighted linear combination of a wide range of risk factors for, and indicators of, problem gambling. They measured not just socio-demographic risk but also the location and utilisation of various mental health services (including problem gambling treatment), the residential location of people utilising homelessness services, and the location of payday-loan outlets and food banks.

The strength of these studies is that they capture the spatial variations of a wide range of gambling-related variables. However, their chief shortcoming is that they are entirely predictive. The outcome variable they produce is a unitless measure of vulnerability, but this index is not calibrated against any empirical data on outcomes *per se*. Consequently, the weights that are assigned to the various elements of vulnerability indices are necessarily arbitrary, with no empirical grounding beyond expert opinion. In effect, they operate in a manner similar to a spatial version of multiple linear regression in which all coefficient values are determined *a priori* by the analyst rather than being estimated from data. At best, the maps produced using this approach provide an educated guess regarding the location and relative prevalence of problem gambling.

This shortcoming is unfortunate given the collection of a large quantity of survey data specifically designed to investigate problem gambling (Williams et al., 2012). The primary limitation of existing surveys that hinders their use in the production of small-area estimates of problem gambling is that they are typically not geocoded (or geocodes are obscured for privacy reasons), so it is difficult to precisely allocate survey responses to residential locations. Even where geocodes are provided, surveys generally do not collect sufficiently spatially-dense data to produce estimates of harm at fine spatial resolutions using regression-based methods such as multilevel modelling (Whitworth et al., 2016).

Other methods such as spatial microsimulation provide an attractive means of producing small area estimates. This paper shows how the strengths of the index modelling approaches discussed above can be combined with well-developed spatial methods to improve small-area estimates. Specifically, spatial microsimulation is used to produce empirically-calibrated small-area estimates of problem gambling that take advantage of spatially-referenced administrative data as well as census data to constrain estimates.

1.2. Improving spatial microsimulation estimates of health outcomes with geographic indicators of risk

Spatial microsimulation provides a suite of methods for geographically allocating survey responses to small spatial areas using well-defined spatial data about the small areas to constrain estimates. The purpose is to synthesise a set of geographically-specific study populations, which can then be further analysed in a manner relevant to the study domain and research questions (Lovelace and Dumont, 2016). In typical usage, spatial microsimulation involves three discrete steps. First, the total counts of persons across different socio-demographic categories are extracted from a population census at the finest possible geographic scale, either as counts of a single census category or as counts from a cross-tabulation of two or more variables. Second, these census-derived totals are harmonised with variables measuring the same construct (e.g. sex, age bracket, etc.) from a survey for which unit record data are available. The outcome variables of interest, which are measured by the survey but not the census, are also identified and included in the unit record data. Third, spatial microsimulation methods are used to allocate survey responses to small areas in a manner that makes the synthesised small-area totals match the census margins as closely as possible. This enables reliable estimates of the outcome variables of interest to be produced at finer geographic scales than those possible using the survey alone.

Spatial microsimulation has been used in this manner to produce small-area estimates of a range of health outcomes. For example, Cataife (2014) combined survey data with census statistics to produce estimates of the prevalence of obesity in tracts spanning just a few city blocks. Similarly, Smith et al. (2011) estimated smoking prevalence in Census Area Units in New Zealand, synthesising a national health survey with census data on four socio-demographic variables. These examples share a standard approach to spatial microsimulation in which survey responses are combined with census data without recourse to other sources of spatial information.

However, the reliability of the estimates produced by these methods depends in large part on the ability of census variables to predict the health outcome of interest. In general, the choice of constraint variables is crucial in producing reliable spatial microsimulation based estimates (Smith et al., 2011). In cases where the outcome measure is strongly related to a small number of census variables or their interactions, spatial microsimulation is likely to produce good results. However, for many policy-relevant problems, the outcome of interest is only poorly correlated with census variables. This makes the use of spatial microsimulation less attractive and suggests a need for further, spatially-referenced constraint variables that may not be provided in population censuses.

Environmental risk factors play a role in mediating many health outcomes and provide a likely candidate for providing such additional information. Variables measuring environmental risk factors (e.g. EGM accessibility) have been incorporated into the problem gambling index models described above (e.g. Conway, 2015; Doran and Young, 2010; Robitaille and Herjean, 2008). In a study aimed at estimating the uptake of gestational diabetes screening in small areas in Ireland, Cullinan et al. (2012) provide an example of how auxiliary spatial information on risk can be used to augment typical spatial microsimulation approaches. Because screening uptake is highly dependent on the spatial accessibility of screening facilities, an application of spatial microsimulation to census data alone would have provided geographically questionable results. Therefore, using geocoded hospital register data, the authors converted absolute spatial measures (i.e. individuals' residential latitude and longitude) into a relative spatial measure (i.e. distance to nearest screening centre) and incorporated this as a constraint variable into their model. They were also able to extract other contextual variables such as urban or rural status for each person in the register on the basis of their residential location. These

Download English Version:

https://daneshyari.com/en/article/5114821

Download Persian Version:

https://daneshyari.com/article/5114821

Daneshyari.com