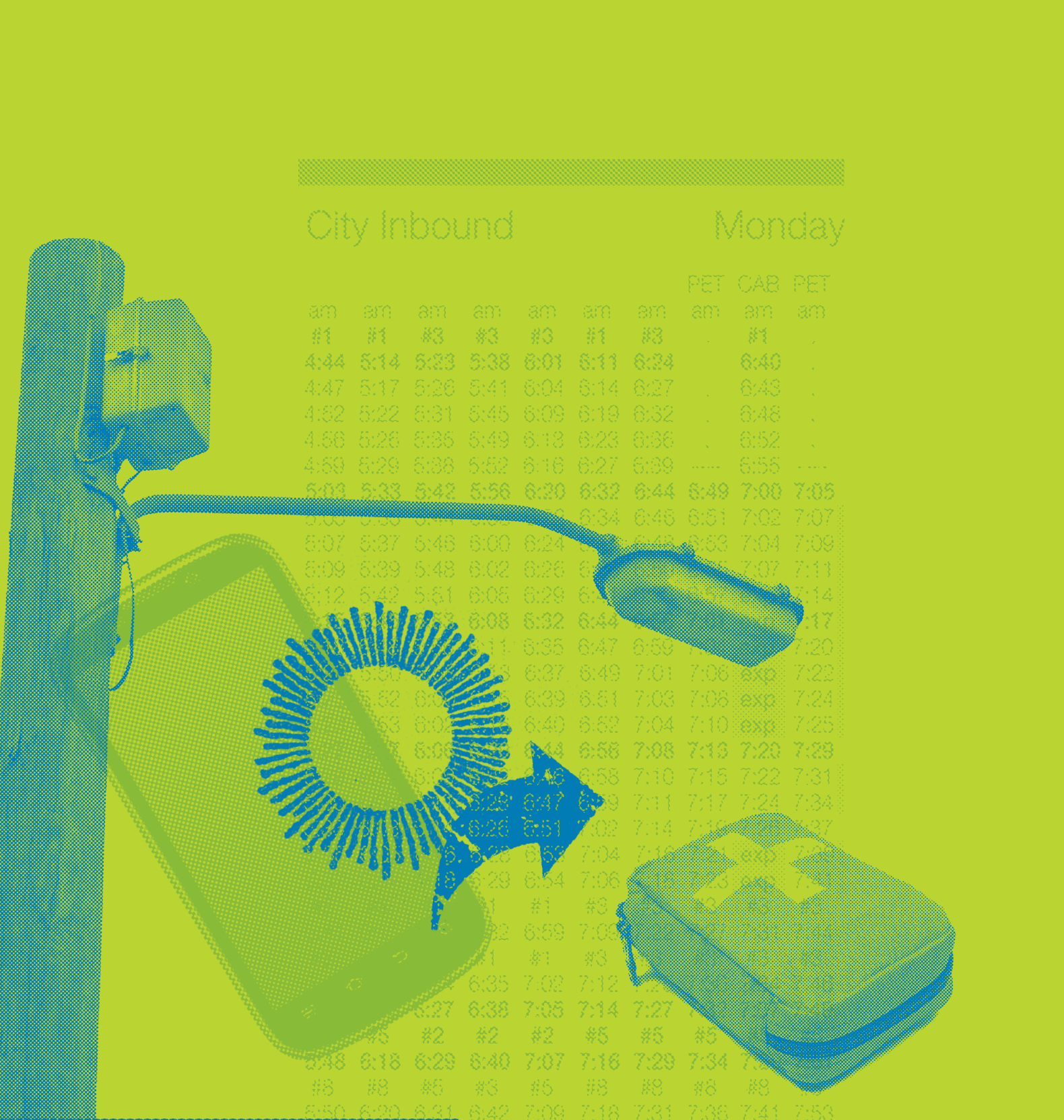




# AN ECONOMIC EVALUATION OF THE HOMELESS TO HOME HEALTHCARE AFTER-HOURS SERVICE

PROFESSOR LUKE CONNELLY





Front Cover: Megan, Homeless to Home  
Healthcare Registered Nurse with Max,  
Brisbane City, April 2013.

Photography: Patrick Hamilton.

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**About the author**

Luke Connelly BA(Econ) MEconSt, PhD (Qld) is an economist who works in applied microeconomics, particularly health economics and insurance economics. He is Professor of Health Economics at The University of Queensland (UQ), Director of the UQ node of the Australian Centre for Economic Research on Health (ACERH), Associate Director of the Centre of National Research on Disability and Rehabilitation Medicine (CONROD), and is an Affiliate Professor with the UQ School of Economics and the UQ Centre for Clinical Research (UQCCR). His recent articles in the peer-reviewed literature include works published in the *Journal of Health Economics*, *Health Economics*, *Social Science and Medicine*, *Review of Income and Wealth*, *Journal of Risk and Insurance*, *Geneva Papers on Risk and Insurance*, *Economics and Human Biology*, *Journal of Clinical Epidemiology*, *Journal of Law and Medicine* and the *Lancet*.

**Contact details**

Professor Luke Connelly  
CONROD, The University of Queensland  
Ground Floor, Edith Cavell Building  
Royal Brisbane and Women's Hospital  
Herston, Queensland, Australia 4006  
Email: l.connelly@uq.edu.au  
Ph: +61 7 3356 5560 | Fax: +61 7 3346 4603

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Dr Jim O'Connell from Boston, USA, joins the Homeless to Home Healthcare After-Hours Service on the streets of Brisbane, May 2012.

Photography: Marc Robertson, The Courier Mail.



# EXECUTIVE SUMMARY

Homeless and vulnerably-housed people tend to have complex healthcare needs. People in this population subgroup are part of the group of vulnerable people that uses hospital emergency departments (EDs) intensively.

For instance, recent evidence collected at an ED in Melbourne over a one-month period shows that homeless people who attended the ED did so at a rate that is consistent with more than 18 visits per annum. That result accords with findings internationally: vulnerable users of EDs commonly represent a small proportion (e.g., 4.5%-8%) of attendees, but a large proportion (e.g., 21%-28%) of ED visits. This result generally obtains irrespective of the particular healthcare financing arrangements (e.g., the extent of public insurance) that are in place.

It is also known that the average inpatient length-of-stay for the homeless and vulnerably-housed population is considerably longer than that of the general population. Recent evidence from the UK, for instance, shows that homeless people have an average length-of-stay that is three times that of the general population and average treatment costs that are approximately four times those of the general population.

Emerging literature shows that moving people who are homeless into housing tends not only in reducing healthcare costs but also in improving health outcomes and quality of life. Provision of healthcare is a critical success factor in a “Housing First” approach which aims to house people as quickly as possible to end their homelessness and to connect them with the community and health services they require. During the period of time in which the Homeless to Home Healthcare After-Hours Service has been operating, at least 227 people have made the transition from being homeless to being housed. One hundred-and-ten of those people also received services from the Homeless to Home Healthcare After-Hours Service.

There is also now considerable literature on the effectiveness and cost-effectiveness of interventions that are designed to improve the efficiency of

healthcare utilisation by this patient subgroup, particularly in respect of ED utilisation. Most of the literature on that topic is concerned with the effect of case management interventions on ED use (e.g., to reduce “unnecessary” ED presentations by people in this vulnerable group). The majority of such studies show that programs of that kind reduce ED use and lead to considerable cost savings without contributing to adverse health outcomes, and sometimes improving them.

This report presents an economic evaluation of the Homeless to Home Healthcare After-Hours Service. The Homeless to Home Healthcare After-Hours Service is a nurse-led outreach and healthcare service that is embedded within a broader “Housing First” approach to homelessness. It integrates nurses with a community-based assertive outreach team called the Street to Home service in order to enable both housing and healthcare responses to be provided in a coordinated manner. Services are provided to individuals in a continuum of care from the point of working with people who live and receive services on the street, to ongoing care through home visits when a person is housed. The Homeless to Home Healthcare After-Hours Service was designed to meet a gap in the healthcare market, providing front-line service delivery to homeless people sleeping rough and home visits to people in temporary accommodation or people who are housed, but have experienced chronic homelessness (i.e., homelessness of a period of six months or more) across the Brisbane metropolitan area.

The report focuses on estimating the impact of the Homeless to Home Healthcare After-Hours Service on ED presentations and hospital inpatient admissions. By adopting this narrow focus, a range of effects of the service are likely to be missed: service provision data suggest that emergency services use (e.g., calls for the ambulance service and police) are

likely to have been reduced by the service and that its liaison with other services (e.g., services such as Murri Watch, which are provided to indigenous people) may also have prevented other costly sequelae, such as incarceration. Similarly, to the extent that access to GP and other services has been facilitated by the service—and data on this aspect of the service and the counterfactual situation (i.e., what would have happened without Homeless to Home Healthcare After-Hours Service) are unavailable—some of the costs generated by the service may be underestimated. By restricting the scope of the analysis to two high-cost hospital-based activities though, this report narrows the focus to the effect of the service on high-cost healthcare use.

## Methods

- In 2010, before the advent of the Homeless to Home Healthcare After-Hours Service initiative, Micah Projects commenced the collection of unit record data from the Brisbane homeless and vulnerably-housed population using an instrument called the Vulnerability Index (VI). Data collection has occurred each year since, including 2013 when the Homeless to Home Healthcare After-Hours Service was operating in a stable and stationary fashion. This study uses a pre-/post- design to analyse unit-record data collected by Micah Projects Inc. (2013) on self-reported hospital use.
- The VI collection includes a range of questions that render it amenable to a study of the effect of the Homeless to Home Healthcare After-Hours Service on inpatient admissions and ED presentations. Furthermore, the VI data contains information on potentially important confounding factors, which include indicators of educational attainment, pension card and healthcare card status, gender and a range of other variables including age. Furthermore, it is argued that other potentially confounding factors—the global financial crisis (GFC) and ED and inpatient waiting times—are unlikely to be responsible for any observed effects of the Homeless to Home Healthcare After-Hours Service on ED and inpatient services use.
- The analysis uses basic statistical comparisons, followed by a range of sophisticated count data regression specifications to estimate the effect of the Homeless to Home Healthcare After-Hours Service on ED and inpatient use by the Brisbane homeless population.

- The best-estimates from these statistical analyses are then used to estimate the cost savings associated with reductions in hospital use and the monetised benefits of health-related quality-of-life improvements, to arrive at an estimate of the net social benefit of the Homeless to Home Healthcare After-Hours Service.

## Main Results

- It is estimated that the Homeless to Home Healthcare After-Hours Service reduced both inpatient admissions and ED presentations in Brisbane:
  - the model-predicted annual inpatient admissions for the cohort fall from 2,136 without the service to between 1,314 and 1,355 with the service.
  - the model-predicted annual ED presentations for the cohort fall from 7,726 without the service to between 5,805 and 5,908 with the service.
  - the costs of hospital use are estimated to fall between \$6.45m to \$6.90m as a result of the Homeless to Home Healthcare After-Hours Service (applying a conservative estimate of the cost per ED and inpatient presentation by this population).
- It is estimated that the annual health-related quality-of-life gains due to the Homeless to Home Healthcare After-Hours Service are:
  - likely to be of the order of at least 82 quality-adjusted life-years per annum
  - have a monetised value of \$6.16m when a conservative estimate of the value of a quality-adjusted life-year is employed.
  - have a monetised value of \$13.49m when the value of a statistical life-year implied by the Office of Best Practice Regulation’s preferred estimate is used.
- It is therefore estimated that the annual net social benefit of the Homeless to Home Healthcare After-Hours Service is:
  - between \$12.61m to \$13.06m when a conservative estimate of the value of a quality-adjusted life-year is employed.
  - between \$20.85 and \$21.97m when the Office of Best Practice Regulation’s preferred estimate of the value of a statistical life-year is used.



Conclusion

The net benefits of the Homeless to Home Healthcare After-Hours Service are positive: its benefits outweigh its costs, whether or not the scope of the evaluation includes only hospital system costs or is extended to include the monetised benefits of improvements in health-related quality-of-life.

The Homeless to Home Healthcare After-Hours Service therefore appears to be in the class of dominant interventions (i.e., that class of interventions that not only improves health, but also does so at lower cost than the alternative). It has been estimated that between 8% and 20% of published evaluation fall into this category, with the remainder of interventions either costing more per unit of health gain, or costing more and producing no additional health gain.

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Homeless to Home Healthcare  
nurturing the home within

A JOINT INITIATIVE OF:



INTRODUCTION

The purpose of this study was to undertake an economic evaluation of an initiative called the Homeless to Home Healthcare After-Hours Service. The service is provided through a collaborative approach where nurses work in conjunction with an outreach team of housing-focused community workers providing outreach directly to people living on the street and making home visits when people who have experienced chronic homelessness are housed.

The nurse-led health response provides direct care and treatment, performs follow-up consultations and works jointly with the community workers to build the trust and rapport that is necessary to assist people to move into housing, to remain housed and get access to appropriate healthcare.

This introduction contains a detailed definition of the target population of the Homeless to Home Healthcare After-Hours Service and of the service itself. This is followed by a brief review of some literature that is germane to the use of health services by this population and of interventions that may affect patterns of healthcare use. The remaining sections of the report are: Data and Methods, Results and Discussion.

The Homeless to Home Healthcare After-Hours Service

The Homeless to Home Healthcare After-Hours Service is a collaborative initiative between Mater Health Services, Micah Projects, Greater Metro South Brisbane Medicare Local, Metro North Brisbane Medicare Local and St Vincent's Private Hospital (Brisbane). The roles of the partner organisations are as follows:

- 1. The Greater Metro South Brisbane Medicare Local and the Metro North Brisbane Medicare Local are the funders of the program and share in its oversight.
- 2. Mater Health Services employs and exercises clinical governance of the service's nursing staff.

- 3. Micah Projects Inc. is the lead agency in the implementation of a multidisciplinary after hours outreach team.
- 4. St Vincent's Private Hospital (Brisbane) is a referral source for the Homeless to Home Healthcare After-Hours Service for aged care and palliative care patients.

The Homeless to Home Healthcare After-Hours Service has a number of elements. At its core is the nurse-led outreach in a multidisciplinary team to people living on the streets, and vulnerable individuals who have been housed. The partners involved in the implementation of the service are entities (1.) to (3.), above. The healthcare service operates from 6pm to midnight, seven days a week (including public holidays) and is integrated with the Street to Home team which operates from 6pm to 2am.<sup>1</sup> Each of these services has two workers who are rostered to form two teams, one of which works in the Street to Home outreach van which typically goes to public spaces, parks and squats. The other team works from a vehicle supplied by the Mater hospital and makes home visits and visits to public spaces across the Brisbane metropolitan area.

The strategic intent of the collaboration is to ensure the rapid re-housing of homeless people and to provide cost-effective healthcare services at all stages of the housing process (i.e., before, during and after re-housing) in order to reduce the personal and social costs and impact of homelessness to the individual and the community.

1. The Street to Home Service is funded by the Queensland State Government under the National Partnership Agreement on Homelessness (NPAH). For further details about the NPAH see Department of Social Services (2014).



The activities of Homeless to Home Healthcare After-Hours Service include:

- collaborative planning and engagement with housing-focused community workers (i.e., the Street to Home team);
- the provision of a single access point to after-hours services including housing and healthcare;
- the establishment of trust and rapport with individuals and families who are homeless as well as vulnerable individuals in housing;
- the provision of an immediate response to people who present to the Brisbane Homelessness Service Centre (BHSC) and outreach in the streets, parks, and homes of people housed through Housing First initiatives;
- the provision of health assessments and referrals to primary healthcare, including allied health, services;
- follow-up of care via supported referral to other practitioners and provision of assistance to navigate the healthcare system;
- engagement in proactive early intervention and preventative healthcare;
- health education; and
- the coordination of healthcare for individuals via liaison and advocacy with local GP clinics and specialist services such as:
  - dental care services;
  - drug and alcohol treatment services;
  - renal services;
  - diabetic services; and
  - vaccination clinics.

The service also liaises with hospitals and hospital workers and the Community Hospital Interface Program (CHIP) nurses about discharge planning and clinical follow-up (Micah Projects Inc. 2014).

### Defining the Target Population

The target population of the Homeless to Home Healthcare After-Hours Service is individuals and families who are currently homeless and individuals who have experienced chronic homelessness and are vulnerable in housing. Homelessness, in this report, is defined according to the definition adopted by the Australian Bureau of Statistics (2012). Briefly, the ABS defines homelessness as follows:

“When a person does not have suitable accommodation alternatives they are considered homeless if their current living arrangement:

- is in a dwelling that is inadequate; or
- has no tenure, or if their initial tenure is short and not extendable; or
- does not allow them to have control of, and access to space for social relations” (Australian Bureau of Statistics 2012, p.7).

The goal of the Street to Home initiative is to re-house people who are homeless—including people who have experienced chronic homelessness—rapidly. Thus the target group for Homelessness to Home After-Hours Service is to both populations of people: those waiting to be housed who are homeless, in temporary accommodation, motels, and those who have been housed. Integrating a healthcare service with housing services is considered a critical component in housing individuals with high-level needs and keeping them housed.

### Hospital Use by People with Experience of Chronic Homelessness

While there is a lack of comprehensive data on the needs of homeless people (Australian Institute of Health and Welfare 2012), it is well-documented that homeless and marginally-housed people are frequent users of hospital emergency departments (EDs): they comprise a relatively small group of vulnerable people who have disproportionately high numbers of ED visits (Mandelberg et al. 2000, Kushel et al. 2001, Kushel et al. 2002, Hansagi et al. 2001, Althaus et al. 2011). Indeed, while frequent users of the ED tend to comprise 4.5%-8.0% of ED patients, they nevertheless account for 21-28% of ED visits (LaCalle and Rabin 2010, Kumar and Klein 2013). This result has been recorded across a range of different countries and seems to obtain irrespective of the type of health system that is in use (Althaus 2011).

Even in countries with universal health insurance provisions, such as Canada and Australia, high levels of unmet healthcare need amongst homeless and marginally-housed people exist. For instance, a large (*n*=1165) study of homeless Canadians (Chambers et al. 2013) has shown that, although the mean number of annual ED visits in this sample drawn from three large Canadian cities was 2.0, high-frequency users of the ED had an average of 12.1 visits per annum. The latter constituted 10% of the sample, but accounted for 60% of the sample’s ED visits. Moore et al. (2012) produced corroborating evidence of the high-frequency use of ED care by homeless people in Australia. Moore and her colleagues collected data on ED visits at a Principal Referral Hospital in Melbourne for a period of one

month. Over the period 1-30 April 2009, 211 homeless people made 327 ED visits, accounting for approximately seven per cent of patients and 10 per cent of visits that month.<sup>2</sup> Ninety of the 211 patients also presented again at the ED within 28 days of discharge from hospital.

A number of recent Australian studies have examined service use by homeless people (Moore et. al 2012), the costs of homelessness, and the benefits produced by interventions to assist homeless and marginally housed people (Zaretsky et. al. 2008, Flatau et al. 2012, Zaretsky et al. 2013, Zaretsky and Flatau 2013).

This section provides a brief overview of the international and Australian evidence of the costs of homelessness and the benefits of interventions that are designed to improve the patterns of healthcare use by this population. Its focus is especially on studies that have considered the costs and consequences of interventions that are designed to affect the use of hospital ED and inpatient services by vulnerable populations, including homeless and marginally-housed people.

### International Literature

There is strong evidence that interventions such as case management and counselling can reduce ED use among high-frequency users (Althaus et al. 2011; Kumar and Klein 2013). In a systematic review of 11 studies of high-frequency ED users, Althaus et al. (2011) located eight studies that considered the effect of case management on ED use. Six of those studies found that ED use decreased significantly as a result of case management, while one showed a significant increase and one showed no statistically significant change in ED use. Three of the studies reviewed by Althaus et al. (2011) explicitly examined the costs and consequences of case management interventions that were designed to reduce ED visits by high-frequency ED users.

Okin et al. (2000) conducted a pilot study of a case management intervention with 53 individuals who were identified as having used the ED of the San Francisco General Hospital more than five times in the preceding 12 months. They found that the median number of ED visits decreased from 15 to nine (*p*<0.01) and that the median ED and inpatient costs each fell (from \$4,124 to \$2195 and from \$8,330 to \$2,786, respectively), resulting

in net cost savings. The authors estimated that, for each dollar invested in the program, the hospital saved \$1.44.

Shumway et al. (2008) conducted a randomised controlled trial (RCT) in which 252 frequent users were randomised between case management (*n*=167) and usual care (*n*=85). They found that the cost of the intervention was similar to that of usual care, but concluded the intervention was cost-effective because it resulted in statistically and clinically significant improvements in psychosocial outcomes.

Wassmer et al. (2008) studied an intervention that was designed to educate frequent users of the ED at the University of California, Davis Health System on how better to use community services as alternatives to the ED. The program was delivered to 157 frequent users of the ED and resulted in fewer annual ED visits and fewer inpatient admissions. The authors estimated that the intervention reduced healthcare costs by nearly \$9m per annum.

In an unpublished, but well-conducted study, Ackeret et al. (2011) conducted a cost-benefit analysis (CBA) of a care coordination system that was introduced in Madison, Wisconsin. That study also produced evidence that the social benefits of the intervention exceeded its costs: the authors estimated the net social benefit was in excess of \$0.5m.

Studies of the effects of housing on cost avoidance also suggest that considerable cost savings tend to accrue to the healthcare system, as well as across other areas such as the justice system. Flaming et al. (2009) used a propensity score-matching design to compare the average costs of 279 matched pairs of homeless and housed (and previously homeless) individuals in Los Angeles. They showed that the average cost of individuals in supportive housing was \$605 per month, while the average costs incurred for their homeless peers was \$2,897 per month. An important driver of this result was the decline in hospital expenditure that was observed between the housed and homeless groups: monthly inpatient expenditures declined by between 82 and 91 per cent (private and public hospitalisations, respectively) and expenditures on outpatient and emergency visits also declined by 87 and 89 per cent, respectively.<sup>3</sup>

2. If the pattern of ED presentations for this month is representative of presentations throughout the year, the mean number of ED presentations expected per annum for this group would be approximately 18.59.

3. A small qualitative study by Cousineau and Lander (2009) used a before-and-after design to review the costs of services used by four homeless LA people for a two-year period before, and a two-year period after they were housed. That study showed that the total cost of services fell by approximately 43 per cent, from \$187,288 for the two-year period before being housed, to \$80,256 for the four individuals studied.



Australian Literature

The Australian literature on the costs of homelessness and the costs and benefits of programs to assist homeless people has developed considerably in the past five years. Prior to the work of Zaretsky et al. (2008), two substantive literature reviews (Berry et al. 2003, Pinkney and Ewing 2006) established the paucity of Australian evidence on the cost of homelessness, and the costs and cost-effectiveness of homelessness prevention and support programs.

Zaretsky et al.’s (2008) work on homelessness in Western Australia sought to quantify the net cost of homelessness programs by estimating the gross cost of those programs and subtracting the costs that are averted as a result. They drew together data from a range of sources, including surveys of homeless people, administrative data, and so on, to estimate the costs and benefits of homelessness programs. Importantly, they restricted the focus of these potential savings to health and justice outcomes to improve the feasibility and reliability of measurement. The authors acknowledged that there still two limitations of their work. First, some of the benefits of homelessness programs fall outside the health and justice systems and these are not measured. Second, to compute the cost savings to the health sector, the authors assumed that the homelessness programs in question would reduce healthcare utilisation to levels commensurate with that of the general population. The authors note that the latter outcome is probably unlikely.

Note, though, that these two potential sources of estimates bias run in opposite directions: there is simply insufficient data available to determine whether or not these limitations—which arise due to a lack of data—are likely to give rise to an under- or over-estimate of the social value of homelessness programs. Zaretsky et al. (2008) estimated that the annual health and justice system costs for homeless people in their sample were, on average, \$10,217 more than the population average. Greater expenditure on hospital visits accounted for the majority (87 per cent) of this total, being \$8,893 per annum greater than the population average.<sup>4</sup>

Flatau et al. (2012) evaluated an intervention by Mission Australia (“The Michael Project”) for Homeless men in Sydney between 2007 and 2010. The intervention involved “...temporary accommodation, or outreach support, assertive case management, and guaranteed

access to a range of specialist services and supports” (p.v). These authors found this program to be cost-saving. In relation to health services in particular, the researchers found that while the fundamental physical and mental health problems of Michael Project clients often remained unchanged, the annual healthcare costs per client fell, on average, by \$8,222 per annum.

In a baseline study, Zaretsky et al. (2013) estimated the differences in non-Specialist Homeless Service (non-SHS) use—defined as healthcare, justice and welfare service use—for the prospective clients of the SHS and the general population. Service use for the prospective clients of SHS was estimated using a baseline client survey. The authors then estimated the costs of service use by respondents and compared them to those of the general population. They estimated that, if non-SHS service use could be reduced to levels commensurate with that of the general population, government expenditure per person would be approximately \$29,450 (AUD2010-11) less per annum. This work was undertaken as a precursor to more extensive study that was designed to estimate how much of these savings might be realised in practice.

The follow-up work by Zaretsky and Flatau (2013) used both a client survey and an agency survey to determine what the impact of SHS on non-SHS costs might be in practice. To answer this question, the authors conducted an evaluation of the costs and consequences of SHS operating in the inner city and metropolitan and major regional centres in New South Wales, Victoria, South Australia and Western Australia over the period 2010-2012. The SHS included:

- supported accommodation programs for single men;
- supported accommodation programs for single women, including women who were escaping domestic violence;
- tenancy support programs for people at risk of losing an existing tenancy; and
- street-to-home programs.

To collect information about non-SHS use and other variables of interest, before and after the provision of SHS, the baseline survey of Zaretsky et al. (2013) was used and a follow-up survey was conducted. The baseline survey was conducted prior to the provision of SHS to respondents, and a follow-up survey 12 months later, after the provision of SHS. The agency survey was used to collect data that would enable the costs of the

SHS at the time the baseline survey was administered to be estimated, using a “bottom-up” approach. The authors also collected data from participating agencies and services and information in the public domain to enable a “top-down” estimate of the costs of homelessness services and for “non-homelessness service use” (i.e., health, justice and welfare services).

The baseline survey focused on circumstances in the 12 months prior the commencement of their current period of homelessness support (n=204), while the follow-up survey was conducted 12 months later. The follow-up survey had a follow-up rate of 30 per cent (n=61). Zaretsky and Flatau (2013) argue that, while the supported accommodation subsample is sufficiently large to be representative of clients of those services, the street-to-home subsample is very small and that the results for those services are provided only for completeness. They note (p.2) that although the respondent characteristics of the follow-up respondents “were not materially different to those who did not participate in that survey”, they caution against placing too much emphasis on the estimates per se, but emphasise instead the direction and relative magnitude of them. As a result of the small sample size for the latter, no cost and cost-offset estimates are produced for street-to-home services.

The authors found that, on average, the potential savings to government for clients of SHS services (other than street-to-home) is \$3,685 per client, per annum. When decomposed by SHS group (i.e., into single men’s services, single women’s services, and tenancy support services), though, the results vary considerably. The largest average net saving (\$8,920 per person, per annum) was for people supported by single women SHS, followed by single men (\$1,389). Services for tenancy support clients, however, were associated with an increased cost of non-SHS of \$1,934 per person. While the savings for single women were driven by large average decreases in healthcare costs (-\$9,295 per person, per annum), reduced justice services costs (-\$6,447 per person, per annum) drove the reduction in costs for men, while mean healthcare costs for single men increased by \$4,460 per person, per annum. Healthcare costs for tenancy support clients also increased considerably by \$3,448 per person, per annum, more than offsetting the lower justice costs (-\$1,934). A substantial reduction in median healthcare costs was found for single women (only).

Overall, the only SHS group for which a cost saving was found by Zaretsky and Flatau (2013) was for single women’s services (-\$4,030 per person, per annum), while the single men’s services and tenancy support services resulted in net costs (\$3,501 and \$3961 per person, per annum, respectively). The authors emphasise that while, overall, services for homeless people result in net savings their sub-group analyses highlight the danger of falling into a “...trap of espousing the simple story that homelessness interventions are immediately highly cost effective for all clients, producing very large cost savings across the board” (Zaretsky and Flatau 2013, p.9).

4. Using the Australian consumer price index (Australian Bureau of Statistics 2013) to inflate these 2008 values to present (AUD2013) values results in a total current price estimate of \$11,764 per homeless person, of which \$10,235 is due to greater hospital utilisation by homeless people.





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Ros, Homeless to Home Healthcare  
Clinical Nurse, visiting Ross in his  
home, August, 2010.

Photography: Mark Riemers.

# METHODS & DATA

This section provides a detailed discussion of the methods and data used in this study. Ultimately, the work required an economic cost-benefit analysis (CBA) (Drummond et al. 2005; Cullis and Jones 2009) to be undertaken. This decision, though, was taken after attempts to build a cost-effectiveness model failed due to a lack of suitable data. The reasons for this and a detailed discussion of the regression-based methods upon which the CBA was built are described below.

## Methodological Considerations and Data Constraints

Two related methodological issues arise in this study. First is the question of which economic approach is the most appropriate to evaluate the Homeless to Home Healthcare After-Hours Service. The second is the availability of suitable data to evaluate the service, which was already in existence when the research was commissioned.

Initially, a Markov Chain model structure was adopted with a view to modelling service use by the homeless and marginally-housed population in Brisbane and the effect of the Hospital to Home Healthcare After-Hours Service on service utilisation, costs and outcomes. The model included the use of an extensive range of services including, but not limited to health and hospital services, and reflected the referral pathways that are recorded in an extensive record of the Hospital to Home Healthcare After-Hours Service’s activities. In an attempt to improve its tractability, that model was subsequently simplified to include only health-related services. That model was then populated using detailed local data on the activities of the Hospital to Home Healthcare After-Hours Service.

An exhaustive search of the literature was also then undertaken in an attempt to populate the unknown parameters of the Markov model. Ultimately, though, this approach was abandoned for two reasons. First, it was determined that insufficient data were available to construct a defensible estimate of the patterns of use of many services (e.g., GP services, ambulance services, and so on) by the target population prior to the introduction of the Hospital to Home Healthcare After-Hours Service. Second, the parameter uncertainty

for the counterfactual in particular was so strong that the usual approaches for dealing with second-order uncertainty (e.g., via Monte Carlo simulation) were unlikely to produce a convincing model. Too many important parameters were still simply unknown.

## Data on Hospital Use

While service use patterns with and without the Hospital to Home Healthcare After-Hours Service were not generally known, there were two important exceptions: data on the use of hospital inpatient and emergency department services were available from samples drawn on Brisbane’s homeless and marginally-housed (hereinafter “homeless”) population. Specifically, in 2010 Micah Projects Inc’s “Street-to-Home” team began surveying the Brisbane homeless population using an instrument developed by Common Ground New York (Micah Projects Inc 2013) to compute a measure of housing need called the Vulnerability Index (VI).

The VI is based on a large case-control study by Hwang et al. (1998) in which the authors constructed a dataset with age-matched paired controls of 558 decedents who had been seen by homeless healthcare service in Boston between 1993 and 1998. The controls in that study were individuals who had also been seen by the program and were still alive at the end of 1993. The items in the VI instrument were generally selected based on quantitative analyses of the attributes that were predictive of lower odds of survival.

The authors used the resulting dataset to estimate the influence of a range of health- and illness-related variables as well as English language fluency on the risk of death for homeless people. The VI is a survey



instrument that is based on those risk factors and others and it includes several questions about healthcare use. In particular, respondents are asked how many times they have been admitted as a hospital inpatient *in the past 12 months* and how many times they have visited the ED *in the past three months*. Micah Projects Inc administered the VI survey to 261 Brisbane homeless people in 2010 and to 105 people in 2013, by August (i.e., at the time this study commenced). Note that, although the sample size in 2013 is less than half that of the 2010 sample, the variables of interest are, by construction, of equal duration. Expressed differently, while fewer people had been surveyed by August 2013 than were surveyed in calendar year 2010, respondents were asked to respond for the same recall periods. Thus, observed differences between these periods are not attributable to truncation or censoring with respect to time.

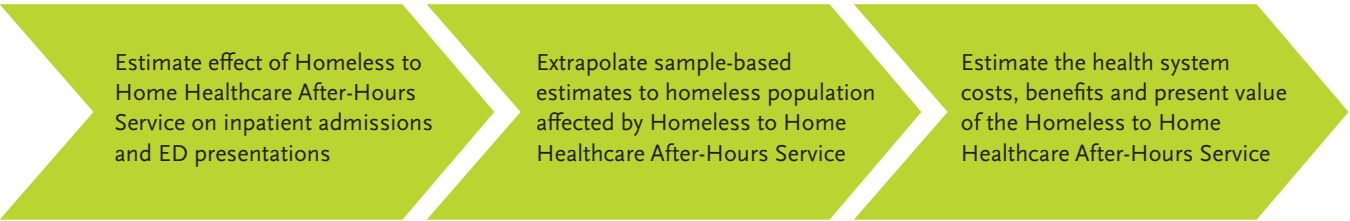
The availability of self-reported data on hospital use enables the construction of a pre-post study design. A disadvantage of this design is that, while it includes all of the costs of the Hospital to Home Healthcare After-Hours Service, by focusing only on hospital use outcomes it excludes from consideration many of the other outcomes produced by the service. In this respect, the pre-post design is conservative: avoided ambulance and other emergency services attendances, incarceration and other outcomes are not included in the estimated social benefit of the service.

Conversely, attributing differences between the period before and after (during) an intervention to the intervention itself assumes that other factors that could also affect the outcomes of interest did not change in the intervening period. It is difficult to prove this to be true due to a lack of data on other variables that could affect hospital use or control data from another jurisdiction, which would facilitate a difference-in-difference regression approach. Nevertheless, consultation with local experts on SHS service provision in Brisbane suggests that other services for homeless people in Brisbane have remained fairly stable in the intervening period. Additionally, because this study depends on sample data, the sample frame and method must have remained the same over time. Since the collection of VI data is by Micah Projects Inc., and is not related to the Hospital to Home Healthcare After-Hours Service *per se*, changes of the latter kind are an unlikely source of bias. A discussion of the validity and accuracy of self-reported health service utilisation is provided below, as is a review of the evidence of the validity of the VI.

The modelling strategy for this study is described by Figure 1. It involves (i) estimating inpatient admissions and ED services with and without the Homeless to Home Healthcare After-Hours Service, (ii) extrapolating utilisation rates to the homeless population that is served by that service, and (iii) estimating the health system costs, benefits and present value of the service.

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**Figure 1**  
**Modelling strategy to estimate the costs and benefits of the Homeless to Home Healthcare After-Hours Service**



**Estimating Inpatient admissions and Emergency Department presentations with and without Homeless to Home Healthcare After-Hours Service**

The first component of the modelling strategy involves estimating the differences in inpatient admissions and ED presentations with and without the Homeless to Home Healthcare After-Hours Service. This component involves extensive econometric work on the estimation of the appropriate (count data) econometric models.

**Possible Confounding Factors**

Ideally, the study design would employ a control group, but one is not available in this case. The availability of a control group—such as a homeless population in another jurisdiction that did not experience the intervention—would enable a difference-in-difference design and provide some reassurance that the intervention, rather than extraneous factors, is responsible for any changes witnessed.

In the absence of a control group it is worthwhile to consider the potential for confounding. Two potential confounders were identified: the global financial crisis (GFC) of 2007-2008 and changes in ED and hospital waiting times. These will now be addressed in turn.

**The Global Financial Crisis of 2007-2008**

If the effect of the GFC was to increase poverty and homelessness in Brisbane it could also conceivably increase the use of inpatient admissions and ED attendances. Unfortunately direct data on changes in the homeless population between 2010 and 2013 are unavailable, as the most recent estimates available are from the Australian Bureau of Statistics (2012a), for 2011. Thus, the only way to consider the potential impact of the GFC is via the distal determinants of homelessness it may have affected, such as unemployment and wealth.

Although the GFC predates the study period, and Australia was not as badly affected by the GFC as many other countries, unemployment rose by nearly two percentage points to 5.75 per cent in November 2009 and the value of equity held by Australian households declined, on average, by 10 per cent by March 2009 (Reserve Bank of Australia 2010). The Australian dollar also declined by nearly 30 per cent from its 2008 peak, but had largely recovered by the end of 2009 and more than half of the equity value losses had been recovered by November 2009 (Reserve Bank of Australia 2010).

By comparison, the unemployment rate in 2013 was very similar: it was 5.7 per cent in July and rose to 5.8 per cent in December (Australian Bureau of Statistics 2014a). The value of the Australian dollar also peaked at above parity with the US dollar in 2012-13. No post-2011 data on household wealth is currently available. On the basis of the available data though, the GFC seems unlikely to have created a shock to homelessness in Brisbane or to ED and inpatient service use by this population.

**Emergency department and hospital waiting times**

Since public patients treated in a public hospital are charged zero fee for treatment, waiting times in large part become the important rationing price. A confounding factor would arise if the waiting times for ED treatment or non-urgent (i.e., “elective”) hospital admissions increased appreciably between 2010 and 2013 or if inpatient admissions more generally have been declining over time.<sup>5</sup>

Data on waiting times for Queensland ED departments and elective surgery admissions are available from the Australian Institute of Health and Welfare (2013a and 2013b). **Table 1** shows ED waiting time data for Queensland and **Table 2** shows elective surgery waiting time data for Queensland. ED waiting times have been declining across all measures. The waiting time for elective admissions has remained virtually constant at the 50th percentile, but has increased at the 90th percentile by approximately 10 per cent. The proportion of elective surgery patients that waited more than one year for surgery in 2012-13 was 0.01 per cent higher than in 2009-10, although in 2010-11 the proportion waiting more than 365 days was 1.2 per cent lower than it was in 2012-13. Thus, if ED use has been affected by lower waiting times, this effect should run counter to that of the intervention: i.e., lower waiting times should encourage more ED use, leading to an under-estimate of its true effect.

The number of inpatient admissions in the three major hospitals that are most likely to admit the homeless and vulnerably-housed population of interest in this report are the Royal Brisbane and Women’s Hospital (RBWH), the Princess Alexandra Hospital (PAH), and the Mater Misericordiae Adult (“Mater Adult”) Hospital. **Table 3** shows that, across these three hospitals inpatient admissions increased by 9,900 between 2009-10 and 2012-13, representing an increase of approximately 5.2 per cent. Notably, both PAH and Mater Adult admissions declined slightly, while the RBWH’s admissions increased by 12,435 (Queensland Health 2014).

5. Less than two per cent of the sample has private health insurance (Micah Projects Inc. 2013) so admission as a private patient is unlikely to be an major source of inpatient use in this sample.



**Table 1**  
**Emergency presentation waiting time statistics, public hospital emergency departments, Queensland, 2009–10 to 2012–13**

	2009–10	2010–11	2011–12	2012–13
Median waiting time (minutes)	24	23	22	18
90th percentile waiting time (minutes)	115	111	103	91
Proportion seen on time (%)	66	67	69	74

**Source:** Australian Institute of Health and Welfare (2013a, Table 3.2).

**Table 2**  
**Waiting time statistics for admissions from waiting lists for elective surgery, Queensland, 2009–10 to 2012–13**

	2009–10	2010–11	2011–12	2012–13
Days waited at 50th percentile	27	28	27	27
Days waited at 90th percentile	147	146	147	163
Per cent waited more than 365 days	2.4	1.3	2.0	2.5

**Note:** Three Queensland Hospitals with more than 10,000 admissions for elective surgery were unable to provide data to the AIHW for three quarters of 2012-2013.

**Source:** Australian Institute of Health and Welfare (2013b, Table 3.2).

**Table 3**  
**Numbers of admitted episodes of care at RBWH, PAH and Mater Adult Hospitals 2009-10 to 2012-13**

	2009–10	2010–11	2012–13
Admitted episodes of care			
RBWH	82,592	89,907	95,027
PAH	86,879	82,151	84,527
Mater Adult	22,052	20,638	21,869
Totals	191,523	192,696	201,423

**Source:** Queensland Health (2014).

It is difficult to determine precisely what this overall growth in inpatient admissions means for per capita hospital inpatient admissions. The Brisbane population grew by approximately six per cent between 2009 and 2012 (Queensland Government Statistician’s Office 2014a), but the inner-city population grew by 5.1 per cent (Queensland Government’s Statistician’s Office 2014b). Although RBWH and PAH are tertiary referral hospitals that treat patients from across the state these results seem to suggest no considerable change in per capita hospital inpatient admissions during the study period. The absence of an obvious, secular, reduction in per capita hospital use also virtually rules out this possible source of confounding.

Extrapolating Utilisation Rates

In the event that null hypotheses (i) or (ii) are rejected, estimates of the resulting differences in ED or inpatient use will be computed. To do so, estimates of utilisation from these samples will be applied to the subset of the homeless population that is currently served by the Hospital to Home Healthcare After-Hours Service. Data supplied by Micah Projects Inc. show that most of the activities of the Hospital to Home Healthcare After-Hours Service fall within a 10km radius of the Brisbane CBD.

As a simplifying and conservative assumption, the effect of the Hospital to Home Healthcare After-Hours Service on utilisation is therefore to be extrapolated only to that part of Brisbane’s homeless population that is estimated, using Australian Bureau of Statistics (2012a) *Census (Estimating Homelessness, 2011)* data to reside within 10km of the CBD. Specifically, this includes the following Statistical Local Areas (SLAs): Brisbane-North, Brisbane-South, Brisbane-West, Brisbane-Inner City, Capalaba, Wynnum Manly and Forest Lake-Oxley. According to these data, there were 2216 homeless and marginally housed people within 10km of the CBD. However, a more precise estimate of the reach of the service was available from Micah Projects Inc.’s Homeless to Home Healthcare After-Hours Service collection: the data suggest that at least 1369 people, identifiable by name, will actually be treated by the service annually.<sup>6</sup>

Estimating Hospital Expenditure

The hospital expenditure estimates in this study use the efficient pricing approach that was introduced with the *National Health Reform Act 2011 (Cth)*, as implemented by the (Queensland) Department of Health (2013) for the 2013-2014 financial year. This report assumes that the efficient prices that have been announced represent the marginal opportunity cost of the resource use associated with these hospital activities.

The Queensland Efficient Price (QEP) for a Queensland Weighted Activity Unit (QWAU) in 2013-2014 is \$4,660 for an inpatient admission. This is the value that is applied to all inpatient admissions in this report. This is likely to be a very conservative estimate: this population sub-group is known to have more complex health problems and longer-than-average lengths of stay than the general population. For instance, in the UK it has been shown that the average length of stay for homeless people is three times that of the general population, and the cost of their treatment is four times that of the general population (Deloitte 2012), while some have estimated the “unscheduled secondary care costs” for homeless people to be eight times that of the general population (Leicester Homeless Primary Health Care Service 2008 in Hewitt and Halligan 2010).

The Independent Hospital Pricing Authority (2013) has examined the influence of homelessness on the cost of admitted mental health inpatient services in Australia. It found that the costs of treating homeless people were approximately 19% higher than those of treating the non-homeless population and that this was driven by a longer average length-of-stay. An estimate of the comparative costs of treating homeless people as inpatients, more generally, in Australia is not available.

The marginal cost of an ED presentation used in this report is \$1,864. This constitutes forty per cent of the QEP for a QWAU and is derived from the average weighted activity units applied by Queensland Health (2012) at one of Brisbane’s large tertiary-referral hospitals. This estimate may under- or over-estimate the marginal cost of an ED presentation by the population of interest in this report. The complex health needs of homeless people may serve to increase the marginal cost of their care in ED. Conversely, if this group is over-represented in presentations for non-acute care at ED, the intensity of the treatment required may be reduced on average. Nevertheless, as Brisbane EDs are

6. This number increases to 1412 when all individuals, including people could not be identified by name, are counted. The more conservative estimate of 1369, however, is used throughout this study.

generally operating at capacity,<sup>7</sup> it is likely that marginal ED users displace other potential users of their services. For the purposes of this report, the assumption that average and marginal costs of ED use are equal to 0.40 (QWAU) is the best available.

Including Health-Related Quality-of-Life Gains

No data currently exist on the Brisbane sample that would enable an estimate of health-related quality-of-life (HRQoL) gains that may have arisen due to the Homeless to Home Healthcare After-Hours Service. Nevertheless, it is reasonable to assume that the services provided via the Homeless to Home Healthcare After-Hours Service will have, relative to the counterfactual, improved the management of disease in this population. In a study of a health intervention for homeless people in Madison, Wisconsin, Ackeret et al. (2011) attempted to account for the improvements in HRQoL that are likely to be associated with disease management in that population. They identified five conditions—hypertension, diabetes, depressive disorder, bipolar disorder and anxiety disorder—that are prevalent in the homeless population and drew estimates of utility differences with managed and unmanaged disease from the peer-reviewed literature. Using estimates of the prevalence of each condition, they then provided estimates of the potential HRQoL gains, expressed as quality-adjusted life-years (QALYs) saved, that would likely be associated with the management of those conditions.

The conditions identified by Ackeret et al. (2011) are known to be prevalent in the Brisbane (Micah Projects Inc. 2013) and, in addition, the Homeless to Home Healthcare After-Hours Service routinely provides a range of services that pertain not only to the treatment of these conditions as well as others (e.g., wound and injury management, medication review). The benefits of these services to consumers of them are not known, but are likely to constitute a source of social benefit. In order to estimate the magnitude of this source of benefit this study applies an unweighted mean of the utility gain estimates used by Ackeret et al. (2011), of 0.12 QALYs. Since this estimate is not based on local data, a more conservative assumption—that the true utility gain is only 0.06 per client whose disease is managed by the

service—will be applied to generate a baseline estimate of the possible health gains due to Homeless to Home Healthcare After-Hours Service.

Monetising Health-Related Quality-of-Life Gains

There has been much debate in the international literature as to how reductions in mortality risk or improvements in health-related quality-of-life should be monetised. In a report for the Australian Government's Department of Finance and Deregulation, Abelson (2008) discusses a range of related issues. Based on the best available evidence at that time, he recommended that Australian policy-makers adopt a range of \$3m-4m (AUD2007) as the value of a statistical life (VSL). The midpoint of this range (i.e., \$3.5m) amounts to a present value of approximately \$176,274 (AUD2013) per life-year for a healthy, prime-aged individual.<sup>8</sup>

Although recent evidence produced by Knieser et al. (2012) on the VSL in the United States suggests that Abelson's (2007) recommendation for Australia is probably conservative, much lower thresholds for a quality-adjusted life-year (QALY) have been observed in the health sector. In Australia, for instance, George et al. (2001) studied the decisions of the Australian Pharmaceutical Benefits Advisory Committee (PBAC) from 1992-1996 and concluded that it was unlikely to recommend interventions with a cost per QALY of \$76,000 (AUD1997) or more for listing and was unlikely to reject interventions with a cost per QALY of \$42,000 (AUD1997) or less for listing. In current (AUD2013) prices, these amounts are approximately \$114,475 and \$64,920, respectively. Thus, although health sector applications of so-called cost-effectiveness thresholds are controversial, for reasons described by, e.g. Gafni and Birch (2006), two lower cost-per-QALY values will also be applied in this report for the purposes of sensitivity analysis. Specifically, estimates of social value due to health gains will be monetised using values of \$75,000 and \$50,000 per QALY in addition to the value implied by Abelson's (2008) recommendation. Using these three values provides estimates of the sensitivity of the results to different assumptions about the value of a QALY.

Accuracy, Validity and Reliability of Self-Report Service Data

Before describing the data and methods in more detail, a fundamental question to address is whether or not self-reported data on service use are likely to be accurate. A considerable literature exists on this question, and a small literature also exists on the accuracy, reliability and validity of self-reported service use by homeless people. One of the difficulties with such comparisons is that there is no “gold standard” against which self-reported utilisation data may be compared. Specifically, it is widely acknowledged (Lubeck and Hubert 2005) that there are liable to be deficits in utilisation data from other sources (e.g., archival data) too. For that reason, most research on the question of the accuracy and validity of self-reported utilisation examines the degree of agreement between self-reported and other sources of utilisation data, including key informants and archival records for instance.

Bhandari and Wagner (2006) conducted a systematic review of 42 studies that sought to compare self-reported health service utilisation with utilisation data from other sources (e.g., administrative data, key informants in provider organisations). These authors were not specifically concerned with homeless respondents, but with the question of how reliable self-reports of service utilisation are more generally. They excluded health service use for diagnostic purposes and studies that were concerned with the accuracy of self-reported medication use. Their results showed that the accuracy self-reported healthcare utilisation is affected by the sample population and its cognitive abilities, the recall time-frames that are used, the type of service that is of interest, the frequency of utilisation, questionnaire design (including how items are worded), the mode of data collection and by the use of memory aids and probes. In the context of the present study, the following findings of Bhandari and Wagner (2006) are particularly noteworthy:

- under-reporting health service utilisation is positively associated with the frequency of utilisation (because people tend to forget some visits as the number of visits rises);
- “stigmatised” healthcare use, such as visits that are ascribable to mental health problems or alcoholism are generally under-reported;<sup>9</sup> and

- “salient visits”, such as inpatient hospitalisations, tend to be more reliably reported than physician and ambulatory care visits.

Low levels of agreement were reported for ED visits in one study (Ungar and Coyte. 1998), but that result may be unreliable. To collect self-reported data on ED visits Ungar and Coyte. (1998) used a question that combined “...emergency room visits, urgent care visits, and hospital outpatient clinic visits in the same category” (p.1340). The authors themselves admit this to be problematic, because outpatient clinic visits are unlikely to be as salient as ED visits, which tend to be less common, generally arise for acute problems, and hence are more likely to be recalled. It is also worthwhile to note that this result comes from a fairly small study of 76 patients with respiratory complaints.<sup>10</sup> The results reported by Petrou et al. (2002) also suggest that self-reported community healthcare use tended to be under-reported, while hospital use was more accurately reported.

Accuracy, Validity and Reliability of Self-Report Service Data in Samples of Homeless People

There is also small literature on the reliability of self-reports of service use and treatment outcomes by homeless people. Some of that literature (Bahr and Houts 1971; Ropers et al. 1985 and Solarz 1986 cited in Calsyn et al. 1993) suggests that self-reports by homeless people are fairly reliable and valid. Calsyn et al. (1993), for instance, compared the self-reported use by 238 mentally ill homeless people against those of key informants from the services of interest. They found that the data obtained showed high levels of agreement and “...strong evidence for the validity of client reports regarding service use” (p.363). They concluded that while having data from numerous sources can strengthen research into homelessness, “...policy makers who must rely solely on self-reports of homeless mentally ill clients can be relatively confident of the conclusions based on such information”. Furthermore, while agreement between clients and key informants were low for some categories of health and dental service use and therapeutic service use, a high level of agreement was found by Calsyn et al. (1993) for reported hospital inpatient and ED use. Later work by Calsyn et al. (1997) showed moderate to good levels of agreement between service utilisation reports by mentally ill

7. This statement is supported by the evidence that the proportions of patients whose length of stay in ED was four hours or less in July-September 2013 were 68% and 73% in the Metro North and Metro South Health and Hospital Service (HHS) regions; this represents an improvement over the July-September 2012 proportions of 54% and 58%, respectively (Queensland Health 2014a).

8. Abelson computes the value of a statistical life-year (VSLY) of approximately AUD151,000, and this has been endorsed by the Department of Finance and Best Practice Regulation, Office of Best Practice Regulation (2008). Applying CPI indexation, this estimate is approximately \$176,274 in current dollars (AUD2013).

9. Some studies have, however, demonstrated an over-reporting of psychiatric visits (Bhandari and Wagner 2006). Lin and Mustard (2002) showed that the odds of over-reporting were statistically significant in subjects who were classified as being highly distressed.

10. Eighty-three subjects were initially enrolled in this study; 76 completed the interview schedule at 6 months.



homeless people and case managers, but lower levels of agreement on other variables (e.g., psychiatric symptoms). Calsyn et al. (1997) also conclude that self-report data from mentally ill homeless people is generally reliable and valid, but that reliability and validity does depend on the type of data that are collected.”

A study by Clifasefi et al. (2011) provides less confidence in the agreement between self-reported and archival public service utilisation data. Clifasefi et al. (2011) drew a sample that consisted of 134 chronically homeless individuals with severe alcohol problems who participated in a “housing first” (Larimer et al. 2009) trial. The authors studied several services including hospital utilisation using recall periods of 30 days and three years. They found only moderate agreement between self-reported hospital use at 30 days and unsatisfactory agreement between self-reported hospital use for the past three years and archival data. It is important to note that three years is an unusually long recall period and that, for inpatient hospitalisation, a 30-days recall period obviously would exacerbate measurement error through forward telescoping. Indeed, the authors found that accounting for forward telescoping (wherein more distant events are incorrectly attributed, by respondents, to the recall period) in their data. By extending the archival data window to 90 days the over-reporting that was observed with a 30-day recall period was reduced by 17 per cent. The authors also note the possibility that public service utilisation data may themselves be subject to errors or omissions and also that participants may have been treated at hospitals other than the study hospital. Tracking chronically homeless people is also problematic and the authors stated that many participants in this study reported using several aliases and also may not have carried any identification at the time of a hospital admission.

Until recently, there had been no published empirical research that has attempted to validate the VI itself. Cronley et al. (2013) recently conducted a “postdictive validity study” to do so. The authors examined whether or not data collected on the VI is predictive of hospitalisations, as recorded in official hospital records. The authors collected VI data from 97 people in Fort Worth, Texas who were receiving homelessness services and compared these with official hospitalisation data from one local hospital, which is the primary indigent care provider in the community. Their results showed that self-reported and official hospitalisation rates were

“strongly, positively correlated” (p.478) in their sample. They also, however, found evidence of under- and over-reporting of hospitalisations by a substantial minority of the sample. For instance, of 72 people with no official hospitalisation record, eight reported one hospitalisation, ten reported 2-4 hospitalisations and five reported five or more hospitalisations. Among 13 individuals who had an official record of one hospitalisation, five reported 2-4 hospitalisations but four reported no hospitalisations. Similarly, of 11 individuals who had official records of 2-4 hospitalisations three under-reported and three over-reported their admissions. A limitation acknowledged by Cronley et al. (2013) is that their study did not include exhaustive health records, such as mental health and substance abuse treatment at other medical centres. They also cite apparently unpublished work from a San Francisco study reported by Kaufman and Craig (2011 cited in Cronley et al. 2013) in which a high degree of reliability was reported when comparisons between self-reported hospital use from the VI were compared with information from multiple sources.

The findings reported in the literature to date are thus mixed, but while there is evidence to suggest some under- and over-reporting, these are likely to be sensitive to recall periods and the sources of comparison data. Mitigating factors (Bhandari and Wagner 2006) are the recall window used by the VI for ED visits (3 months), and the salience of hospital inpatient stays. Exacerbating factors in this population include mental health problems and substance abuse. It is not currently possible to assess the degree of measurement error that is likely to exist between self-reported and the true latent service use in the current sample. It is important to note, though, that unless the attendant measurement error is time-varying, comparisons between time periods will still be valid. Specifically, although the absolute estimates of hospital use and expenditure may be measured with error, changes in the absolute estimates may still be estimated validly from these data. There is no reason to expect the nature of self-reported measurement error to have changed over the study period, and the maintained hypothesis in this report is that it has not.

11. The authors also note they are only able to report on agreement between client and case manager reports and that they do not have a mechanism for determining whether clients or managers file more “accurate” reports.



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Liz, Homeless to Home Healthcare  
Clinical Nurse with a patient in the  
Street to Home van, October 2012.

Photography: Katie Bennett, Embellysh.



Statistical Analysis of Utilisation Counts

Recall that the modelling strategy is to test the null hypotheses of (i) no differences in the counts of ED visits in 2013 and 2010; and (ii) no differences in counts of inpatient hospital visits in 2010 and 2013. The analysis starts with simple comparisons of the distributions of both types of hospital use and then proceeds to multivariate regression analysis.

The general structure of the ED presentations model for regression analyses is as follows:

ed\_i = alpha + X\_i' beta + epsilon\_i (1)

where ed\_i is the annual count of emergency department presentations for the i-th individual, X is a vector of observed individual characteristics age, age squared, and binary indicators of whether or not the person holds a pension card, whether or not the person holds a healthcare card, the level of educational attainment (as measured by the highest year of schooling obtained) and gender and the presence or absence of the Homeless to Home Healthcare After-Hours Service; alpha is an intercept term; beta is a vector of parameters to be estimated; and epsilon\_i is a stochastic error term. The hypothesis test of interest is on the coefficient estimate for the Homeless to Home Healthcare After-Hours Service: a negative and statistically significant coefficient indicates a reduction in ED use due to the service.

The structure of the inpatient admissions model is:

inpat\_i = alpha + Z\_i' beta + epsilon\_i (2)

where inpat\_i is the number of inpatient admissions for the i-th individual and Z is a vector of observed individual characteristics that includes the annual count of ED presentations, age, age squared, and binary indicators of whether or not the person holds a pension card, whether or not the person holds a healthcare card, the level of educational attainment (as measured by the highest year of schooling obtained) gender, and the presence or absence of the Homeless to Home Healthcare After-Hours Service; alpha is an intercept term; beta is a vector of parameters to be estimated; and epsilon\_i is a

stochastic error term. The hypothesis test of interest is again on the coefficient estimate for the Homeless to Home Healthcare After-Hours Service: a negative and statistically significant coefficient indicates a reduction in ED use due to the service.

Note that (1) and (2) include the quantities of inpatient admissions and ED presentations, respectively, as regressors. The rationale is that these services are likely to be related, probably as economic complements, although some substitution may also occur. In a traditional demand framework, the own-prices and the prices of related goods would usually be included rather than quantities and, for zero-priced goods, transaction (including time) prices would be used. Quantities are used in preference to prices here for two reasons. First, quantities are available at the unit-record level. Second, the time prices that can be constructed apply to only two years in this study: the implication is that every subject interviewed in 2010 would be assigned a single price for each service type and every subject interviewed in 2013 would be assigned a single price for each service type. The available quantity data are richer than a price index constructed from aggregate data would be and are not prone to matters of judgement (e.g., whether and how to weight the time prices recorded for different hospitals in the study catchment), gaming and so on.<sup>12</sup>

The remaining regressors are of secondary interest but the rationale for their inclusion is discussed below, in the presentation of descriptive statistics on the dataset used for the study. A detailed discussion of the related count data econometric issues follows.

Descriptive Statistics

Table 4 presents the summary statistics for the variables used in this study. There is a maximum of 367 observations in the dataset: up to 261 observations in the 2010 sample and up to 106 in the 2013 sample, depending on the variable. It is immediately apparent that the mean numbers of inpatient admissions and ED visits are lower in the 2013 sample which was collected during the operation of the Homeless to Home Healthcare After-Hours Service. Mean inpatient services per capita were reported to be 1.56 per annum and 0.96 per annum before and during the Homeless to Home

Healthcare After-Hours Service respectively and mean ED presentations are 1.41 and 1.06, respectively.<sup>13</sup> The variance in the latter year is, notwithstanding the considerably smaller sample size, also lower for both variables although not substantially so. These two variables are of central interest in this study and it is appropriate to examine their characteristics in considerable detail before turning the remaining variables.

Table 5 provides the quartile values for inpatient admissions and ED presentations. The median for inpatient admissions fell from one to zero between 2010 and 2013 and the third quartile fell from two to one. The medians for ED presentations are equal, but the third quartile fell from eight in 2010 to four in 2013.

Figure 2 plots the counts of inpatient visits for the pre-Homeless to Home Healthcare After-Hours Service (i.e. 2010) and Homeless to Home Healthcare After-Hours Service (i.e. 2013) samples as horizontal bar charts. The values of zero and one on the y-axis indicate the absence and presence of the Homeless to Home Healthcare After-Hours Service, respectively. The datum at the end of each bar indicates the proportion of the sample that had that count. For instance, the first horizontal bar in the Figure shows that 47 per cent of the pre-Homeless to Home Healthcare After-Hours Service sample had zero self-reported counts of inpatient admissions.

These data are also presented in Table 6, along with frequencies by count. Recall that the sample sizes are different, so it makes sense to use sample percentages rather than frequencies to compare them graphically. The first striking characteristic of Figure 1 is the difference in zero counts between the pre-Homeless to Home Healthcare After-Hours Service sample and the sample taken during the operation of the H2H intervention: the proportion of the sample that had no ED visits increased from approximately 47 per cent to approximately 62 per cent. Second, both distributions have long tails, but the tail of the pre-H2H sample is

somewhat heavier, indicating more high-frequency inpatient services use by the pre-H2H sample. These data show that, by comparison with the general population, this sub-group has very high levels of hospital use. The National Health Performance Authority (2013) reports that in 2011-2012 the percentage of adults in the general population who reported any admission to hospital varied from 10% to 21% across Medicare Local populations nationally.

Figure 3 and Table 7 present counts of ED presentations for the with- and without-Homeless to Home Healthcare After-Hours Service samples. The differences between these counts are less pronounced: the proportion of zero counts increases from approximately 52 per cent to approximately 58 per cent. Nevertheless, summing across the first three count categories (i.e., 0-2 ED visits per annum) this lower end of the distribution accounted for 80% of respondents in 2010 and 89% of respondents in 2013. These ED data also demonstrate the high level of ED use in this sub-population: by comparison, the proportions of the general population that reported using an ED in the past was between 8% and 29% across Medicare Local catchments (National Health Performance Authority 2013).<sup>14</sup>

Tables 8 and 9 present the results of nonparametric Mann-Whitney-Wilcoxon (MWW) rank sum tests of the hypotheses of no differences in the distributions of hospital service utilisation in the pre-Homeless to Home Healthcare After-Hours Service period and during the Homeless to Home Healthcare After-Hours Service intervention. Unlike other commonly-applied tests, such as independent sample t-tests, these tests do not assume that the underlying data are normally distributed.<sup>15</sup> The z-test applied in Table 4, on inpatient services, rejects the null hypothesis at the one per cent level (p=0.005) and an inspection of the rank sums shows that the pre-intervention sample is of higher rank. This suggests that hospital inpatient utilisation was indeed lower following the introduction Homeless to Home Healthcare After-Hours Service intervention.

12. Interestingly, some of the heavily-cited count data estimates of demand (e.g., Mullahy 1986; Winkelmann 2004; Deb and Trivedi 2002) also do not contain prices *per se*. This is also true of the “doctor visits” regressions in Cameron and Trivedi (2010) and which, like the specifications in Winkelmann (2004) and Deb and Trivedi (2002) contain indicators of insurance status, but not prices.

13. The median number of inpatient admissions in the 2010 sample is 1.00 and the median in the 2013 sample is 0.00. The medians for ED presentations were 2.00 and 1.00, respectively. During the period 2010-2011 to 2012-13, admitted occasions of service in the top 33 Queensland public hospitals increased by approximately eight per cent; over the same period, the number of non-admitted occasions of service for this group of hospitals declined by approximately three per cent (Queensland Health 2014b, 2014c).

14. These estimates by the National Health Performance Authority (2013) are based on analyses of the Australian Bureau of Statistics’ (2012) *Patient Experience Survey 2011-2012*, in which 26,437 adults were asked to recall their health service use and experience over the past 12 months.

15. Elduff et al. (2010) point out that the application of MWW tests may still be problematic and lead to incorrect conclusions when applied to highly-skewed and zero-inflated series. They advocate regression approaches instead, and such approaches are subsequently applied in this report.



The results in **Table 8** suggest that the null hypothesis of no difference in the distributions of ED services cannot be rejected at conventional levels ( $p=0.179$ ). In relation to the remaining variables in **Table 4**, the following sample characteristics are worth noting:

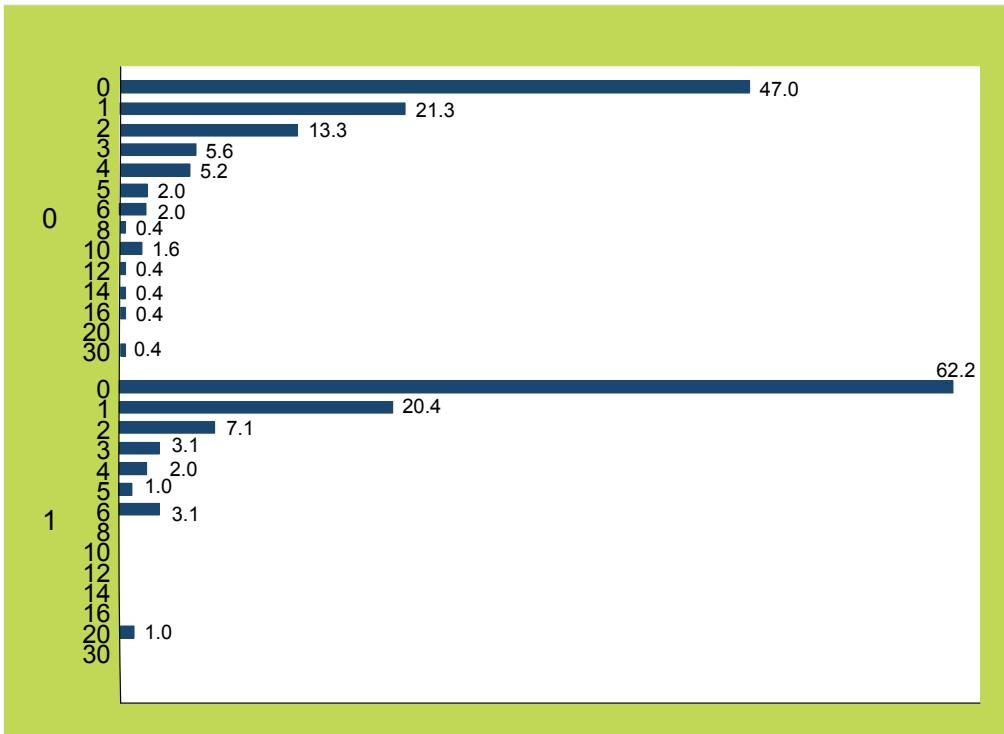
- There is a slightly higher representation of males (78%) in the 2013 sample than the 2010 sample (72%);
- Similar proportions of the samples have previous experience of incarceration (“Prison”);
- The two samples have similar mean ages;
- A larger proportion of the 2013 sample (84%) reported having a healthcare card than the 2010 sample (74%);

- A larger proportion of the 2013 sample (61%) reported having a pension card than did so in the 2010 sample (51%);
- A larger proportion of the 2010 sample (82%) completed year 9 of school or higher than the 2013 sample (77%).

The largest and most noteworthy differences here are (i), (v) and (vi). It is not clear, *a priori*, whether the higher prevalence of holding a healthcare card or a pension card should increase or decrease either inpatient or ED service use, nor of the direction of effect of higher levels of education.

**Figure 2**

Counts of self-reported inpatient admissions in the past 12 months with and without Homeless to Home Healthcare After-Hours Service



**Note:** y-axis labels are “0=Without Homeless to Home Healthcare After-Hours Service”; “1=With Homeless to Home Healthcare After-Hours Service”

**Table 4**  
Summary Statistics

Variable	Pre-Homeless to Home Healthcare After-Hours Service (2010)						Homeless to Home Healthcare After-Hours Service (2013)					
	Obs.	Mean	Std. Dev.	Min	Max		Obs.	Mean	Std. Dev.	Min	Max	
Number of inpatient admissions	249	1.56	2.96	0	30		98	0.96	2.38	0	20	
Number of ED presentations	246	5.64	9.54	0	64		100	4.24	8.62	0	60	
Male: % Yes	261	0.72	0.45	0	1		106	0.78	0.41	0	1	
Prison: % Yes	257	0.49	0.50	0	1		101	0.50	0.50	0	1	
Age	259	43.64	12.83	18	82		105	42.58	12.12	18	73	
Serious health condition: % Yes	261	0.70	0.46	0	1		106	0.63	0.48	0	1	
Health care card: % Yes	256	0.74	0.44	0	1		99	0.84	0.37	0	1	
Pension card: % Yes	257	0.51	0.50	0	1		106	0.61	0.49	0	1	
Highest year of school 9 or 10: % Yes	224	0.48	0.50	0	1		97	0.37	0.49	0	1	
Highest level of school 11 or 12: % Yes	224	0.34	0.48	0	1		97	0.40	0.49	0	1	

**Notes:** (i) All data are self-reported, with the exception of with the exception of “Serious health condition” which was reported as Yes or No by the person administering the questionnaire if a serious health condition was evident; (ii) ED presentations are emergency department presentations, annualised from reported ED use in the past three months; (iii) Obs. is the number of available (i.e., non-missing) observations; and (iv) Std. Dev is the standard deviation.

**Table 5**  
Quantiles of self-reported inpatient admissions and emergency department presentations in the past 12 months, with and without Homeless to Home Healthcare After-Hours Service

	Minimum	First quartile	Median	Third Quartile	Maximum
Inpatient admissions without H2H	0	0	1	2	30
Inpatient admissions with H2H	0	0	0	1	20
ED presentations without H2H	0	0	0	8	16
ED presentations with H2H	0	0	0	4	15

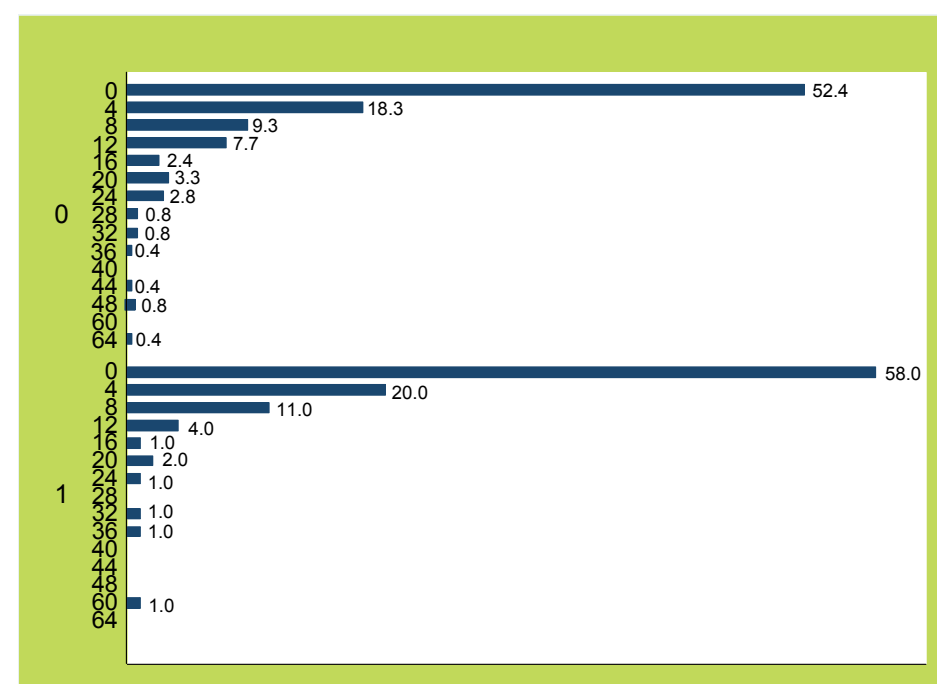
### Table 6

### Counts of self-reported inpatient hospital admissions over the past 12 months, with and without Homeless to Home Healthcare After-Hours Service

	Pre-Homeless to Home Healthcare After-Hours Service (2010)			Homeless to Home Healthcare After-Hours Service (2013)		
Count	Frequency	Percentage	Cumulative Percentage	Frequency	Percentage	Cumulative Percentage
0	117	46.99	46.99	61	62.24	62.24
1	53	21.29	68.27	20	20.41	82.65
2	33	13.25	81.53	7	7.14	89.80
3	14	5.62	87.15	3	3.06	92.86
4	13	5.22	92.37	2	2.04	94.90
5	5	2.01	94.38	1	1.02	95.92
6	5	2.01	96.39	3	3.06	98.98
8	1	0.40	96.79	0	0.00	98.98
10	4	1.61	98.39	0	0.00	98.98
12	1	0.40	98.80	0	0.00	98.98
14	1	0.40	99.20	0	0.00	98.98
16	1	0.40	99.60	0	0.00	98.98
20	0	0.00	99.60	1	1.02	100.00
30	1	0.40	100.00	0	0.00	100.00
Total	249	100		98	100	

### Figure 3

### Counts of emergency department presentations with and without Homeless to Home Healthcare After-Hours Service



**Note:** y-axis labels are “0=**Without** Homeless to Home Healthcare After-Hours Service”; “1=**With** Homeless to Home Healthcare After-Hours Service”.

### Table 7

### Counts of self-reported emergency department hospital visits over the past 12 months, with and without Homeless to Home Healthcare After-Hours Service

	Pre-Homeless to Home Healthcare After-Hours Service (2010)			Homeless to Home Healthcare After-Hours Service (2013)		
Count	Frequency	Percentage	Cumulative Percentage	Frequency	Percentage	Cumulative Percentage
0	129	52.44	52.44	58	58.00	58.00
4	45	18.29	70.73	20	20.00	78.00
8	23	9.35	80.08	11	11.00	89.00
12	19	7.72	87.80	4	4.00	93.00
16	6	2.44	90.24	1	1.00	94.00
20	8	3.25	93.50	2	2.00	96.00
24	7	2.85	96.34	1	1.00	97.00
28	2	0.81	97.15	0	0.00	97.00
32	1	0.41	97.56	1	1.00	98.00
36	0	0.00	97.56	1	1.00	99.00
40	2	0.81	98.37	0	0.00	99.00
44	1	0.41	98.78	0	0.00	99.00
48	2	0.81	99.59	0	0.00	99.00
60	0	0.00	99.59	1	1.00	100.00
64	1	0.41	100.00	0	0.00	100.00
Total	246	100	100	116	100	100

### Table 8

Two-sample Mann-Whitney-Wilcoxon rank-sum test of self-reported inpatient hospital admissions over the past 12 months, with and without Homeless to Home Healthcare After-Hours Service

	Obs.	Rank sum	expected
dvH2H=0 (Without Homeless to Home Healthcare After-Hours Service)	249	45513	43321
dvH2H=1 (With Homeless to Home Healthcare After-Hours Service)	98	14865	17051
Combined	347	60378	60372
Unadjusted variance	707658.00		
Adjustment for ties	-103341.74		
Adjusted variance	604316.26		
H <sub>0</sub> : inpat(dvH2H=0)=inpat(dvH2H=1)			
z=	2.813		
Pr> z =	0.005		

**Notes:** (i) Obs. is the number of observations; (ii)  $H_0$  is the null hypothesis the number of inpatient admissions before the intervention is equal to the number of inpatient admissions with the intervention.



**Table 9**  
**Two-sample Mann-Whitney-Wilcoxon rank-sum test of self-reported emergency department visits over the past 12 months, with and without Homeless to Home Healthcare After-Hours Service**

	Obs.	Rank sum	expected
dvH2H=0 (Without Homeless to Home Healthcare After-Hours Service)	246	43715	42681
dvH2H=1 (With Homeless to Home Healthcare After-Hours Service)	100	16317	17350
Combined			
Unadjusted variance	711350		
Adjustment for ties	-117927		
Adjusted variance	593422		
H <sub>0</sub> : inpat(dvH2H=0)=inpat(dvH2H=1)			
z=	1.342		
Pr> z =	0.179		

**Notes:** As for Table 8.

In Australia, the use of public hospital ED and inpatient services as a public patient attract zero user charges, irrespective of whether or not one holds a healthcare card. Thus, whether or not one holds a healthcare card should not *directly* affect ED or inpatient use. Having a healthcare card may, however, reduce the out-of-pocket prices of private fee-for-service (FFS) medical services (which are subsidised under the Medicare Benefits Schedule) and reduces out-of-pocket charges for pharmaceuticals (which are subsidised under the Pharmaceutical Benefits Schedule). Thus, healthcare card holders may be more likely to substitute general practitioner (GP) care for ED services (e.g., for non-urgent and after-hours care). While it is also possible that healthcare card holders are more likely to seek inpatient treatment as a private patient, this seems generally unlikely and especially unlikely in the homeless population.

Many doctors in Australia bulk-bill pension card holders (Department of Human Services 2014), meaning that they are also faced with no out-of-pocket payment, so holding a pension card may also indirectly affect ED use for similar reasons. The receipt of a pension is also, however, typically an indicator of low levels of income and wealth and hence may be positively associated with the hospital variables of interest.

Finally, the effect of education is difficult to predict. Higher levels of education are generally associated with better health, but that association may be associated with higher or lower levels of service use. For instance,

if more highly-educated people seek treatment more readily but are also generally healthier, the sign of the association between education and health service use is indeterminate.

Econometric Issues

The objective of the analyses is to choose a distribution and a model that best characterise the observed counts. In this case, the intervention of interest is the provision of the Homeless to Home Healthcare After-Hours Service and the response variables are ED visits and inpatient hospital stays. These are both count variables (i.e., they are non-negative integer random variables) and specifications that account for their distributional properties are appropriate. Count regressions are nonlinear models that accommodate the discrete nature of the response variable and the attendant feature of its probability distribution, which is a probability mass only at non-negative integer values (Cameron and Trivedi 2010).

The complications associated with count data modelling include the existence of unobserved heterogeneity related to omitted variables, the small mean of the response variable due to the presence of many zeros and sometimes an “excess” of zeros, and endogenous regressors (Cameron and Trivedi 2010). A number of different approaches to these problems have been devised and are well-described in the literature (see, e.g. treatments by Cameron and Trivedi 1998, 2005,

2010 and Winkelmann 2008). Typically, model choice involves both theoretical considerations regarding the nature of the data-generating process(es) (DGPs), the distribution of the response variable of interest, and “...trade-offs between fit, parsimony, and ease of interpretation” (Cameron and Trivedi 2010, p.598). In reality, uncertainty about the DGPs in practice is pervasive (Staub and Winkelmann 2013) and much of the choice of model is of the nature of the trade-offs Cameron and Trivedi (2010) describe. This is the case in this study: a number of candidate models are theoretically justifiable and hence are tested on the data with a view to choosing the most appropriate candidate from the set that is available.

Seven candidate model types were used to model ED inpatient visits and covariates obtained from the VI samples taken in 2010 and 2013. The modelling strategy was to estimate and compare each of the potentially-appropriate specifications using goodness-of-fit as well as the other diagnostic and model selection criteria described by Cameron and Trivedi (2010). Also see Lindsay and Stewart (2008) for a discussion of mixture models.

The candidate models used in this study included (i) Poisson, (ii) negative binomial (NB2), (iii) Poisson hurdle, (iv) NB2 hurdle, (v) two-part (logit-Poisson) finite mixture (FMM2-P), (vi) zero-inflated Poisson and (vii) zero-inflated NB2 models.<sup>16</sup>

Briefly, the rationale for invoking both the non-hurdle (i)-(ii) and hurdle (iii)-(iv) count specifications here is to enable different assumptions about behaviour that is related to hospital use to be reflected in the model specification. This approach is commonly adopted in the econometric literature on health-affecting behaviour, in which it often seems warranted to model the decision to engage in an activity (e.g., to visit a doctor, to smoke) and the intensity of the activity (e.g., number of doctor visits, number of cigarettes smoked) as separate, albeit related decisions.<sup>17</sup>

In the NB2 model, the heterogeneity variable is assumed to have a continuous (gamma) distribution. An alternative is to invoke a discrete representation of unobserved heterogeneity, thus giving rise to a sub-class of latent-class models (Cameron and Trivedi 2010) called FMMs (Cameron and Trivedi 2005, Deb 2007). A simple example of this is the FMM2-P model estimated here. The advantage of this specification is that it allows for the possibility that there are two different “types” of consumers in the sample. For instance, there may be a subgroup of consumers that are particularly high-frequency users of hospital services, and others who rarely seek treatment at a hospital. The motivation for estimating (v) on both ED and inpatient services is to allow for that possibility.

In addition to a visual inspection of the distributions of ED and inpatient visits and the use of the Akaike information criterion (AIC) and Schwarz’s Bayesian information criteria (BIC) to choose between models, this study uses the user-written prcounts and countfit (Long and Freese 2006) routines in STATA v.12 (StataCorp 2011) to compare the goodness-of-fit of the Poisson and negative binomial specifications of the estimated models. For detailed contemporary discussions of these and other aspects of count data modelling see Cameron and Trivedi (2010) and Winkelmann (2008). Also see Cameron and Trivedi (1998 and 2005).

16. The user-written hnplogit and hnblogit (Hilbe 2005a, 2005b) commands were also used in this work. Attempts were also made to estimate negative binomial specifications of the FMM, but these specifications were inestimable. This may indicate a either a failure of identification or fragile identification of the mixture components (Cameron and Trivedi 2010, p.599). It is acknowledged that zero-inflated negative binomial and Poisson specifications are not robust to specification error and generally are not recommended for use in small samples, although the literature is not clear on what actually constitutes a small sample. The zero-truncated specifications are also typically not recommended for small samples but, once again, the literature is evidently silent on what constitutes a small sample. See, e.g. UCLA Statistical Consulting Group (2014).

17. Zero-inflated Poisson and negative binomial specifications may also be applied in such situations, but because they are not robust to misspecification (Staub and Winkelmann 2013) they are typically not recommended for application in small datasets (UCLA Statistical Computing Group 2014), and are not applied here for that reason. Staub and Winkelmann (2012) propose the use of Poisson quasi-likelihood estimators as an alternative and produce Monte Carlo simulation evidence in support of their use in moderate-to-large samples.





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Erin, Homeless to Home Healthcare Registered Nurse and Judy with Noel from the Street to Home team, September 2013.

Photography: Katie Bennett, Embellysh.

# RESULTS

## Regression Results

Seven models were tested on the inpatient admission and ED presentation data. **Table 10** presents summaries of the performance of the inpatient admissions and ED presentations models on goodness-of-fit criteria. Note that smaller values of the AIC and BIC are to be preferred, because larger log likelihood values are preferred. The BIC imposes a larger penalty on model size and is generally considered to be better than the AIC, especially when parsimony is important (Cameron and Trivedi 2010).

For the inpatient models, the AIC is minimised by the FMM2-P model, while the BIC is minimised by the NB2 model. In addition, the results of the NB2 are easier to interpret and use for the purposes of this study. For the ED presentation models the NB2 hurdle model is favoured by both the AIC and BIC. Before considering the marginal effects of interest, further attention will be devoted to a discussion of the fit of these models to the data, because the pseudo-R<sup>2</sup> measures of fit that are routinely reported for such models are arguably of little value.

**Table 10**  
Goodness-of-fit criteria for seven models of inpatient admissions and seven models of emergency department (ED) presentations

Model	Log likelihood	Akaike Information Criterion (AIC)	Schwarz's Bayesian Information Criterion (BIC)
<b>Inpatient admissions</b>			
Poisson	-520.72	1059.45	1093.55
NB2	-400.71	825.42	869.66
Poisson hurdle	-399.83	843.65	924.77
NB2 hurdle	-390.32	826.64	911.44
FMM2-P	-384.24	814.48	899.28
Zero-inflated Poisson	-408.55	857.10	930.97
Zero-inflated NB2	-383.79	809.59	887.16
<b>ED presentations</b>			
Poisson	-1522.81	3067.61	3108.17
NB2	-658.73	1341.46	1385.71
Poisson hurdle	-743.71	1527.42	1601.29
NB2 hurdle	-579.45	1200.89	1278.46
FMM2-P	-742.65	1531.29	1616.09
Zero-inflated Poisson	-743.71	1527.42	1601.29
Zero-inflated NB2	-577.91	1201.83	1286.63

**Notes:** (i) The Poisson model uses the robust (or sandwich) estimator of variance; (ii) NB2 is the negative binomial regression model with gamma heterogeneity, (iii) the Poisson hurdle model comprises a logit regression and zero-truncated Poisson regression, (iv) the NB2 hurdle model comprises a first-stage logit model and comprises a logit regression and zero-truncated NB2 regression, (v) FFM2-P is the two-part finite mixture model comprising a logit regression and a Poisson regression.



Table 11  
Actual and average predicted probabilities from the NB2 model for inpatient admissions (full sample)

Model	Maximum Difference	At Value	Mean  Difference	
NB2	-0.014	1	0.007	
NB2 model: actual and predicted probabilities				
Count	Actual	Predicted	Difference	Pearson
0	0.52	0.52	0.00	0.00
1	0.22	0.23	0.01	0.24
2	0.11	0.11	0.01	0.10
3	0.05	0.05	0.01	0.14
4	0.04	0.03	0.01	1.65
5	0.01	0.02	0.01	0.70
Sum	0.95	0.95	0.05	2.82

Note: Computed using the user-written countfit (Long and Freese 2006) command.

Table 12  
Actual and average predicted probabilities from the NB2 model for emergency department presentations (full sample)

Model	Maximum Difference	At Value	Mean  Difference	
NB2	-0.024	1	0.012	
NB2 model: actual and predicted probabilities				
Count	Actual	Predicted	Difference	Pearson
0	0.55	0.54	0.01	0.04
1	0.19	0.21	0.02	0.78
2	0.10	0.10	0.01	0.18
3	0.06	0.05	0.01	0.61
4	0.02	0.03	0.01	0.90
5	0.03	0.02	0.01	2.89
Sum	0.95	0.96	0.07	5.40

Note: Computed using the user-written countfit (Long and Freese 2006) command.

Table 13  
Predicted probabilities from the NB2 model of inpatient admissions with and without the Homeless to Home Healthcare After-Hours Service

	Without Homeless to Home Healthcare After-Hours Service	With Homeless to Home Healthcare After-Hours Service
Rate:	1.04	0.67
Pr(y=0 x):	0.48	0.59
Pr(y=1 x):	0.26	0.25
Pr(y=2 x):	0.13	0.10
Pr(y=3 x):	0.07	0.04
Pr(y=4 x):	0.03	0.01
Pr(y=5 x):	0.02	0.01

Note: Calculated using the user-written prcounts (Long and Freese 2006) routine in Stata.

Table 14  
Predicted probabilities from the NB2 model of emergency department presentations with and without the Homeless to Home Healthcare After-Hours Service

	Without Homeless to Home Healthcare After-Hours Service	With Homeless to Home Healthcare After-Hours Service
Rate:	1.06	0.81
Pr(y=0 x):	0.52	0.58
Pr(y=1 x):	0.23	0.22
Pr(y=2 x):	0.12	0.10
Pr(y=3 x):	0.06	0.05
Pr(y=4 x):	0.03	0.02
Pr(y=5 x):	0.02	0.01

Note: Calculated using the user-written prcounts (Long and Freese 2006) routine in Stata.

**Tables 11 and 12** present data on how well the NB2 models on inpatient admissions and ED presentations fit the data, using the user-written countfit (Long and Freese 2006) command. The countfit procedure produces the proportions of model-predicted counts alongside the proportions actually found in the dataset.<sup>18</sup> For instance, at the zero count, the inpatient model predicts a probability of 0.52 which is precisely equal to the zero-count fraction in the full dataset.<sup>19</sup> The ED presentations model predicts a zero-count probability of 0.54, while the zero-count fraction in the dataset is 0.55. The accuracy of prediction over the remaining counts is also high and according to the data presented in the first rows of these Tables, the mean difference between model-predicted and actual probabilities are 0.007 and 0.012 for the inpatient and ED models, respectively.<sup>20</sup>

Another way to compare the model fit is by implementing the user-written prcounts (Long and Freese 2006) routine, which compares the model-predicted and actual probabilities of counts. **Tables 13 and 14** present this comparison for the first six counts. The results confirm that the models are a close fit to the data: the mean difference between the predicted and actual count for the inpatient model is 0.007, while the mean difference for ED model is 0.021. Recall too, that the NB2 hurdle—which has a considerably lower BIC to the NB2 specification—has been chosen to calculate the AMEs for ED services. Thus, the fit of the ED model upon which the results will be based is even better than is suggested by the NB2 (non-hurdle) results reported in **Tables 12 and 14**.<sup>21</sup>

**Tables 15 and 16** present the regression results of the NB2 and NB2-hurdle models of inpatient admissions and ED presentations, respectively. The parameter estimates for the inpatient model are reported at the top of the table, while the bottom panel reports the average marginal effects (AMEs), computed using the delta method (Feiveson 2005). This approach is used as averaging the individual effects is preferred when the sample size is relatively small (Greene 1997, p.876 in SAS 2014). Note that Table 16 contains parameter

estimates for both the logit and the zero-truncated Poisson model components of the model, summary statistics are reported for each component separately and overall model fit statistics reported at the bottom of the table. All AMEs were computed using factor notation in Stata v.12 (StataCorp 2011).

The  $\chi^2$  tests for both models show that they are highly statistically significant ( $p=0.00$ ). The low pseudo- $R^2$ s of the NB2 model and zero-truncated Poisson models—0.11 and 0.06, respectively—are typical in cross-sectional analyses such as these, while the pseudo- $R^2$  for the logit component of the hurdle model (0.21) is fairly sizeable. (The statistics reported in **Tables 10 through 14** are, however, more useful indicators of fit.) The summary statistics for both models include an estimate of the over-dispersion parameter  $\alpha$ , and a likelihood ratio test of the hypothesis that  $\alpha=0$ . The likelihood ratio test is rejected at the one per cent level ( $p=0.00$ ) and the addition of the overdispersion parameter improves the model considerably by comparison with the Poisson specification. Cameron and Trivedi (2010) show that  $\alpha$  may also be interpreted as the variance of heterogeneity, and its addition in these models leads to substantial improvements in the log likelihood, as shown by comparing the log likelihoods of the Poisson and NB2 specifications in **Table 10**. The BIC also improves considerably for both the inpatient and ED models as a result of the addition of this one parameter.

**Table 15**  
NB2 regression model of self-reported inpatient visits in the past 12 months

Variable	Coefficient	Standard Error	z	Pr> z
Number of ED presentations	0.28	0.04	6.69	0.00
Homeless to Home Healthcare After-Hours Service: Yes=1	-0.43	0.20	-2.20	0.03
Serious health condition: Yes=1	0.27	0.19	1.40	0.16
Pension card holder: Yes=1	0.43	0.19	2.23	0.03
Health care card holder: Yes=1	0.20	0.20	1.00	0.32
Male: Yes=1	-0.29	0.18	-1.57	0.12
Highest year of school 9 or 10: % Yes=1	0.18	0.24	0.73	0.47
Highest level of school 11 or 12: % Yes=1	0.17	0.26	0.67	0.50
Age	-0.02	0.04	-0.57	0.57
Age <sup>2</sup>	0.00	0.00	0.15	0.88
Intercept	0.09	0.91	0.10	0.92
/ln $\alpha$	-0.14	0.20		
$\alpha$	0.87	0.18		
Number of observations	295			
LR $\chi^2$ (10)	102.64			
Prob > $\chi^2$	0.00			
Pseudo- $R^2$	0.11			
Likelihood ratio test of $\alpha=0$ : $\bar{\chi}^2(01) = 91.41$ Prob>= $\bar{\chi}^2 = 0.000$				
Log Likelihood: -400.71 ;Akaike Information Criterion: 825.42; Schwarz's Bayesian Information Criterion: 896.66				
Average Marginal Effects (Delta Method)				
	dy/dx	Standard Error	z	Pr> z
Number of ED presentations	0.42	0.12	3.43	0.00
Homeless to Home Healthcare After-Hours Service: Yes=1	-0.57	0.24	-2.35	0.02
Serious health condition: Yes=1	0.38	0.25	1.50	0.13
Pension card holder: Yes=1	0.63	0.29	2.18	0.03
Health care card holder: Yes=1	0.29	0.28	1.03	0.30
Male: Yes=1	-0.45	0.30	-1.49	0.14
Highest year of school 9 or 10: % Yes=1	0.27	0.37	0.73	0.47
Highest level of school 11 or 12: % Yes=1	0.27	0.41	0.65	0.52
Age	-0.03	0.01	-2.02	0.04

18. The countfit routine does not currently support the hnblogit command, so the non-hurdle version of the model for ED services is presented here for illustrative purposes.

19. This procedure is performed on the model estimated over the entire dataset, so the fraction of zeros is a weighted average of those in the 2010 and 2013 samples.

20. Recall that the NB2-hurdle model is a better fit than the NB2 (non-hurdle) model and will be used for the estimation of marginal effects. The NB2 results are reported here for information because the countfit procedure does not currently support the hurdle specification of the model.

21. The prcounts and countfit commands may currently be applied only to Poisson and NB2 specifications. A countfit comparison of those two specifications also confirmed that the NB2 was a superior fit to these overdispersed data.



Table 16

NB2 hurdle regression model of self-reported emergency department presentations in the past 12 months

Variable	Coefficient	Standard Error	z	Pr> z
<b>Logit</b>				
Number of inpatient presentations	0.81	0.13	6.04	0.00
Homeless to Home Healthcare After-Hours Service: Yes=1	-0.03	0.31	-0.11	0.91
Serious health condition: Yes=1	0.39	0.30	1.32	0.19
Pension card holder: Yes=1	0.14	0.30	0.47	0.64
Health care card holder: Yes=1	0.67	0.34	1.98	0.05
Male: Yes=1	0.00	0.32	-0.01	1.00
Highest year of school 9 or 10: % Yes=1	-0.73	0.37	-1.96	0.05
Highest level of school 11 or 12: % Yes=1	-0.39	0.38	-1.03	0.30
Age	0.02	0.07	0.33	0.74
Age²	0.00	0.00	-0.21	0.83
Intercept	-2.01	1.55	-1.30	0.20
Number of observations	295			
LR $\chi^2$ (10)	84.79			
Prob > $\chi^2$	0.00			
Pseudo R²	0.21			
Number of inpatient presentations	0.06	0.02	3.32	0.00
Homeless to Home Healthcare After-Hours Service: Yes=1	-0.22	0.14	-1.56	0.12
Serious health condition: Yes=1	0.24	0.15	1.62	0.11
Pension card holder: Yes=1	-0.12	0.13	-0.91	0.36
Health care card holder: Yes=1	-0.33	0.16	-2.09	0.04
Male: Yes=1	-0.16	0.14	-1.14	0.26
Highest year of school 9 or 10: % Yes=1	0.28	0.17	1.63	0.10
Highest level of school 11 or 12: % Yes=1	0.34	0.17	1.96	0.05
Age	-0.01	0.03	-0.24	0.81
Age²	0.00	0.00	0.43	0.67
Intercept	2.27	0.76	3.00	0.00
/lnα	-1.02	0.17		
α	0.36	0.06		
Number of observations	295			
LR $\chi^2$ (10)	56.29			
Prob > $\chi^2$	0.00			
Pseudo R²	0.06			
Likelihood ratio test of α =0: $\overline{\chi^2}$ (01) = 160.35 Prob>=: $\overline{\chi^2}$ = 0.000				
Log Likelihood: -579.44; Akaike Information Criterion: 1200.89;				
Schwarz's Bayesian Information Criterion: 1278.46				

Table 16 Continued

Average Marginal Effects (Delta Method)				
	dy/dx	Standard Error	z	Pr> z
<b>Logit</b>				
Number of ED presentations	0.15	0.02	8.02	0.00
Homeless to Home Healthcare After-Hours Service: Yes=1	-0.01	0.06	-0.11	0.91
Serious health condition: Yes=1	0.07	0.05	1.33	0.19
Pension card holder: Yes=1	0.03	0.06	0.47	0.64
Health care card holder: Yes=1	0.12	0.06	2.07	0.04
Male: Yes=1	0.00	0.06	-0.01	1.00
Highest year of school 9 or 10: % Yes=1	-0.13	0.07	-2.03	0.04
Highest level of school 11 or 12: % Yes=1	-0.07	0.07	-1.05	0.29
Age	0.00	0.00	0.70	0.49
<b>Zero-truncated Poisson</b>				
Number of ED presentations	0.65	0.21	3.06	0.00
Homeless to Home Healthcare After-Hours Service: Yes=1	-2.22	1.35	-1.65	0.10
Serious health condition: Yes=1	2.42	1.41	1.71	0.09
Pension card holder: Yes=1	-1.32	1.49	-0.89	0.37
Health care card holder: Yes=1	-3.89	2.07	-1.88	0.06
Male: Yes=1	-1.73	1.57	-1.10	0.27
Highest year of school 9 or 10: % Yes=1	3.04	1.92	1.58	0.11
Highest level of school 11 or 12: % Yes=1	3.88	2.13	1.82	0.07
Age	0.06	0.06	0.93	0.35

The main estimates of interest for analytical purposes are the AMEs on “Homeless to Home Healthcare After-Hours Service” retrieved from the inpatient admissions and ED presentations models. The AME for the inpatient model is estimated to be -0.57: the interpretation of this marginal effect is that inpatient admissions are reduced by 0.57 visits per capita per annum in this cohort by the Homeless to Home Healthcare After-Hours Service. This AME is statistically significant at the five per cent level ( $p=0.02$ ). The effect size is similar to that observed by Sadowski et al. over 18 months in a housing trial for homeless people that lowered inpatient admissions by approximately 0.50 in the intervention group. **Figure 4** provides a graphical depiction of the estimated effect of the service on inpatient admissions with 95% confidence intervals.

**Table 17** shows that the model-predicted number of inpatient admissions per capita without the Homeless

to Home Healthcare After-Hours Service is 1.63 and 1.05 per capita with the service. The estimated AMEs for ED presentations in **Table 16** are -0.01 for the logit and -2.22 for the zero-inflated Poisson component of the model. The former estimate is suggestive of a small reduction in the probability of ED use with the Homeless to Home Healthcare After-Hours Service, but it is not statistically significant. The latter suggests that the count of ED services is 2.22 less per annum with the Homeless to Home Healthcare After-Hours Service than it is without the service and is marginally statistically significant at the ten per cent level ( $p=0.10$ ).

**Figure 5** provides a graphical depiction of the estimated effect of the Homeless to Home Healthcare After-Hours Service on ED presentations with 95% confidence intervals and **Table 18** shows the predicted service utilisation with and without the Homeless to Home Healthcare After-Hours Service for individuals with

non-zero-counts. Specifically, **Table 18** and **Figure 5** are based only on the zero-truncated NB2 result (i.e., taking the logit estimate of the AME on Homeless to Home Healthcare After-Hours Service to be zero). The estimated effect is broadly consistent with the size of the effect size of a case management program in Okin et al. (2000); although in that study only high-use individuals—as opposed to any individual with a non-zero count—were targeted and the results were based on a median reduction (from 15 to nine) in the number of ED presentations. It is also consistent with the result from Sadowski et al., considering the effect size in that study was -1.20, but that this represents the mean difference between the intervention and control groups (i.e., not only those individuals with positive counts).

Cost-Benefit Analysis: Input Table

The input parameters for the cost-benefit analysis (CBA) are reported in **Table 19**. Estimated numbers of services per capita with and without Homeless to Home Healthcare After-Hours Service include the mean-difference approach and regression estimates that were described in detail above. All other input parameters are as previously described.

Cost-Benefit Analysis: Results

The results of the CBA are reported in **Tables 20-22**. **Table 20** contains estimates of health systems costs with and without the Homeless to Home Healthcare After-Hours Service, while **Table 21** presents the estimated HRQoL gains under two assumptions and three valuations of the willingness to pay (WTP) for a QALY. **Table 22** reports the net social benefits of the Homeless to Home Healthcare After-Hours Service, showing the summation of health system savings and monetised QALY gains under each QALY gain and monetised value assumption.

Inpatient admissions are estimated to be reduced by between 781 and 822 admissions per annum, saving between \$3.64m and \$3.83m per annum. ED presentations are estimated to fall by between 1,813 and 1,916 admissions per annum with the Homeless to Home Healthcare After-Hours Service, resulting in health system savings of between \$3.32m and \$3.57m. Subtracting the annual cost of the Homeless to Home

Healthcare After-Hours Service (i.e., \$503,022) from these inpatient- and ED presentation-based savings produces a net present value of the Homeless to Home Healthcare After-Hours Service of between \$6.45m and \$6.90m per annum. Thus, assuming that the Homeless to Home Healthcare After-Hours Service improves the HRQoL of people treated by it leads to the conclusion that the service is dominant (i.e., cost-reducing and health-improving).<sup>22</sup> This result is quite uncommon to observe: typically, health-improving interventions come at an increased marginal cost. Weinstein et al. (2008), for example, showed that less than 20% of the 599 economic evaluations they reviewed, published between 2000 and 2005, were cost saving. Dalziel et al. (2008), by contrast, found that of the 245 Australian cost-effectiveness results since 1966 they reviewed, only 8% were dominant.

**Table 21** presents the estimated HRQoL gains and their monetised values. Due to the speculative nature of the QALY gains and the wide range of WTP values that is used for sensitivity analysis, these estimates cover a wide range. The minimum value of HRQoL gains is estimated to be of the order of \$4.11m, while the maximum is approximately \$27.79m per annum. A fairly conservative estimate of the probable QALY gains is obtained by assuming 0.06 QALY gains per treated person and setting the WTP for a QALY value as \$75,000. This combination of assumptions gives rise to HRQoL gains of approximately \$6.16m per annum.

The net social benefits of the Homeless to Home Healthcare After-Hours Service are presented in **Table 22**. These are derived by summing the estimated health system savings (**Table 20**) and monetised HRQoL gains (**Table 21**). Once again, the wide range of monetised QALY benefits assumed for sensitivity analysis causes these estimates also to cover a wide range. The lowest estimate of net social benefits estimated is \$10.56m, and the highest estimate is \$35.69m. Adopting the fairly conservative estimate of \$6.16m per annum of HRQoL gains referred to above, the estimated net social benefit of Homeless to Home Healthcare After-Hours Service is between \$12.61 and \$13.06m. Note, though, that adopting the recommendation of Abelson (2008) and the Department of Finance and Best Practice Regulation, Office of Best Practice Regulation (2008) of \$175,274 per QALY, the estimate of net social benefit increases to between \$21.85m and \$21.29m per annum.

22. Note that even if a zero effect of the Homeless to Home Healthcare After-Hours Service was assumed for ED services on the basis of their marginal statistical significance—although this logic is arguably flawed (Gelman and Stern 2006)—the benefits of the Homeless to Home Healthcare After-Hours Service are still estimated to exceed its costs by a factor of more than six.

Figure 4  
NB2 model-predicted inpatient admissions with and without the Homeless to Home Healthcare After-Hours Service

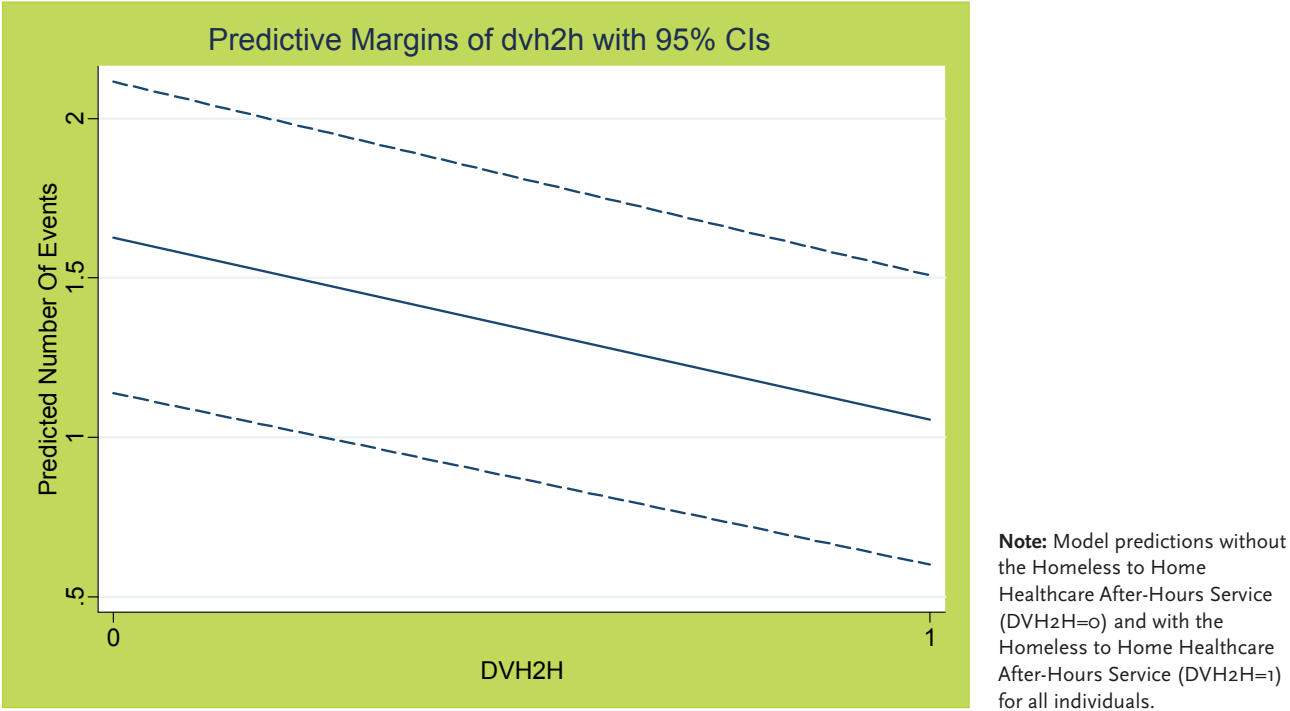
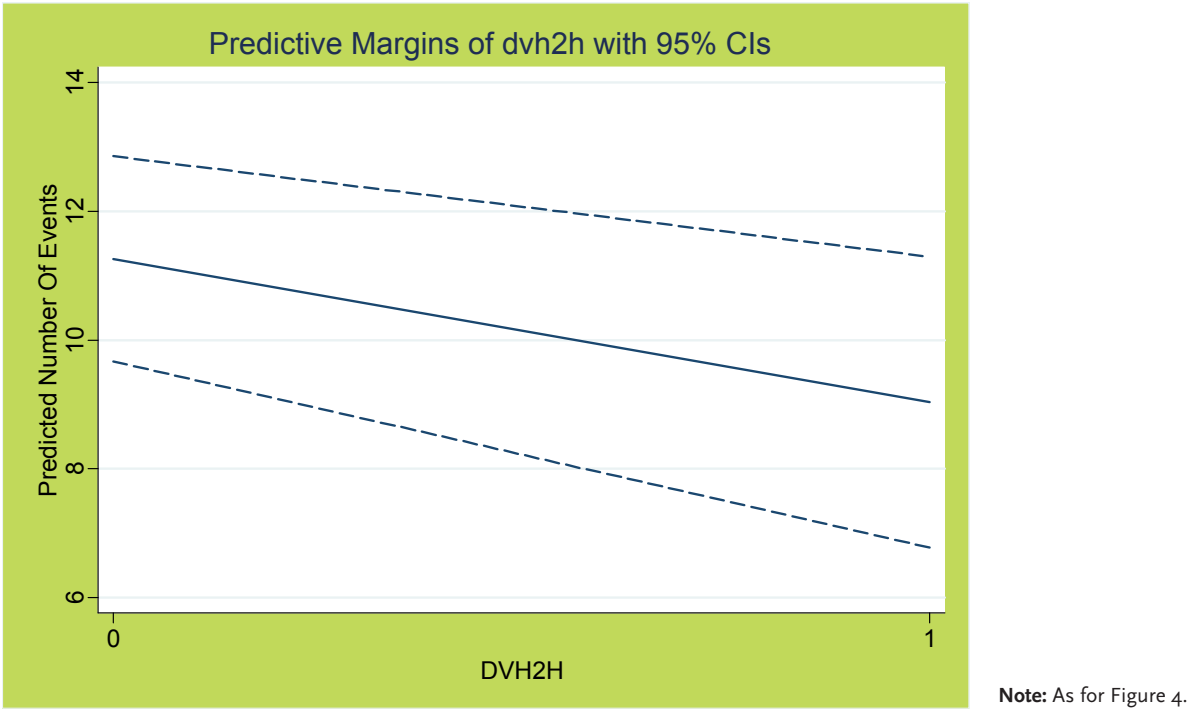


Figure 5  
Zero-truncated NB2 model-predicted emergency department (ED) presentations per capita with and without the Homeless to Home Healthcare After-Hours Service





**Table 17**  
**Model-predicted annual inpatient admissions per person with and without Homeless to Home Healthcare After-Hours Service (Average Marginal Effect)**

	Margin	Std Error	z	Pr>z
Without Homeless to Home Healthcare After-Hours Service	1.63	0.27	6.53	0.00
With Homeless to Home Health-care After-Hours Service	1.05	0.23	4.56	0.00

**Table 18**  
**Model-predicted annual emergency department presentations for individuals with non-zero-ED-counts with and without Homeless to Home Healthcare After-Hours Service (Average Marginal Effect)**

	Margin	Std Error	z	Pr>z
Without Homeless to Home Healthcare After-Hours Service	11.29	0.88	12.85	0.00
With Homeless to Home Health-care After-Hours Service	8.99	1.26	7.12	0.00

**Note:** Computed based on the average marginal effect of the zero-truncated Poisson component of the NB2 hurdle model (only).

**Table 19**  
**Economic evaluation inputs table**

Variable	Without Homeless to Home Healthcare After-Hours Service (1)	With Homeless to Home Healthcare After-Hours Service (2)	Marginal Effect Estimate (3)	Source
Inpatient admissions per homeless person, per annum	1.56	0.96 0.99	-0.60 -0.57	Mean difference NB2 model: average marginal effect
ED presentations per homeless person, per annum	5.64 11.69	4.24 8.99	-1.40 -2.30	Mean difference (all counts) NB2 hurdle model: average marginal effect (applies to non-zero counts)
Incremental quality-adjusted life-years per treated person, per annum	0	0.12 0.06	0.12 0.06	Ackeret et al. (2011) (unweighted mean) Assumption
Number of homeless people in scope	2216	2216	0.00	Australian Bureau of Statistics (2012a) and Micah Projects Inc. (2013)
Number of people homeless treated	1369	1369	0.00	Micah Projects Inc. (2013)
Willingness to pay for a life-year	\$175,247 \$75,000 \$50,000	\$175,247 \$75,000 \$50,000	0.00 0.00 0.00	Abelson (2008), indexed to AUD2013 Assumption Assumption
Cost per inpatient admission	\$4,660	\$4,660	0.00	Queensland Health (2013)
Cost per ED presentation	\$1,864	\$1,864	0.00	Queensland Health (2013)
Cost of Homeless to Home Healthcare After-Hours Service	\$0	\$503,022	\$503,022	Micah Projects Inc. (2013)

**Notes:** # This marginal effect is computed on the zero-truncated negative binomial component of the NB2 hurdle model and pertains only to that part of the sample with non-zero ED utilisation (i.e., 48% of the sample in 2010). Hospital admission and ED presentation rates in column (2) are computed by subtracting the marginal effect listed in column (3) from the mean number of visits listed in column (1) (e.g., at the second row of data: 1.56-0.57=0.99). Indexation of the Abelson (2008) recommendation was undertaken using consumer price index data for Australia (Australian Bureau of Statistics 2014b).

**Table 20**  
Estimated annual health sector costs, benefits and present value of the Homeless to Home Healthcare After-Hours Service

		Without Homeless to Home Healthcare After-Hours Service (A)		With Homeless to Home Healthcare After-Hours Service (B)	
	Common quantities	Common costs	Count per capita	Total count	Total costs
	Cohort	Cost per occasion of service (\$)			
	(n)				(\$)
<i>Health System</i>					
Inpatient admissions	1369	4,460	1.56	2,136	9,952,082
ED presentations	1369	1,864	5.64	7,721	14,392,452
Homeless to Home Healthcare After-Hours Service					10,819,700-11,072,840
Total cost					503,022
					C <sup>B</sup> =16,944,058 to 17,388,585
Net present value (NPV)	Health system benefits less costs of Homeless to Home Healthcare After-Hours Service: (C <sup>A</sup> -C <sup>B</sup> )=6,452,718 to 6,897,244				

Note: Some figures are affected by rounding.

**Table 21**  
Estimated annual monetised benefit of potential quality-adjusted life-year (QALY) gains due to the Homeless to Home Healthcare After-Hours Service under two assumptions about the QALY gain per treated individual, and three values of willingness to pay for a QALY

Assumed mean QALY gain per client	QALY gains by cohort	Assumed Value of a Statistical Life Year (VSLY) (\$)	Monetised QALY gains (\$m)
0.12	164	50,000	8,214,000
	164	75,000	12,321,000
	164	175,247	28,789,577
0.06	82	50,000	4,107,000
	82	75,000	6,160,500
	82	175,247	14,394,789

Note: As per Table 20.

**Table 22**  
Estimated societal net benefit of the Homeless to Home Healthcare After-Hours Service under different assumptions about quality of life gains and willingness to pay for a quality-adjusted life-year (QALY)

Assumed mean QALY gain per client	Assumed Value of a Statistical Life Year (VSLY) (\$)	Monetised QALY gains (\$)	Present Value (Health System Savings) (\$)	Social Net Benefit (\$)
0.12	50,000	8,214,000	6,452,718-6,897,244	14,666,718-15,111,244
	75,000	12,321,000	6,452,718-6,897,244	18,773,718-19,218,244
	175,274	28,789,577	6,452,718-6,897,244	35,242,295-35,686,822
0.06	50,000	4,107,000	6,452,718-6,897,244	10,559,718-11,004,244
	75,000	6,160,500	6,452,718-6,897,244	12,613,218-13,057,744
	175,274	14,394,789	6,452,718-6,897,244	20,847,507-21,292,033

Note: As per Table 20.





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Eva, Homeless to Home Healthcare  
Clinical Nurse on duty with Shelley  
from the Street to Home team,  
March 2013.

Photography: Erin Ebert.

# DISCUSSION

The best estimates of the Homeless to Home Healthcare After-Hours Service’s impact show that its benefits exceed its costs by a wide margin.

This result is robust even to conservative estimates about the effects of the intervention on HRQoL—indeed, it obtains even if such effects are assumed away—because net health system savings alone are estimated to be of the order of \$6.45m to \$6.90m per annum. The reason these are likely constitute conservative estimates because the unit prices of inpatient hospitalisation and of ED presentations were assumed to be equal to one and 0.40 QWAUs, respectively. It is well-known, though, that this population tends to have complex health needs, longer-than-average lengths of stay and higher treatment costs than the general population.

A conservative estimate of the monetised value of probable HRQoL improvements due to the Homeless to Home Healthcare After-Hours Service is between \$6.16m and \$14.39m, depending upon whether or not the WTP for a QALY is assumed to be \$75,000, or a value of \$175,274 is used. The latter figure is the present value of the valuation endorsed by the Department of Finance and Deregulation Office of Best Practice Regulation (2008).

The net social benefit of the service which is the sum of health system cost reductions and monetised QALY gains is estimated to be between \$12.61-\$21.26m. Even at the lower end of this range of estimates, this is an extraordinary return on investment.

## Limitations

The main limitation of this study is that it was necessary to use an observational dataset with a pre-/post- design to study the intervention. It was possible to identify potential confounders and rule out their likely influence on the result. As randomisation to an intervention of this kind is unlikely to be feasible, alternative study designs, such as cross-jurisdictional designs should be considered for future work. Including data collected from another jurisdiction in which no intervention occurs would create a quasi-experimental design, which would permit the use of a difference-in-difference type approach to these measurement problems.



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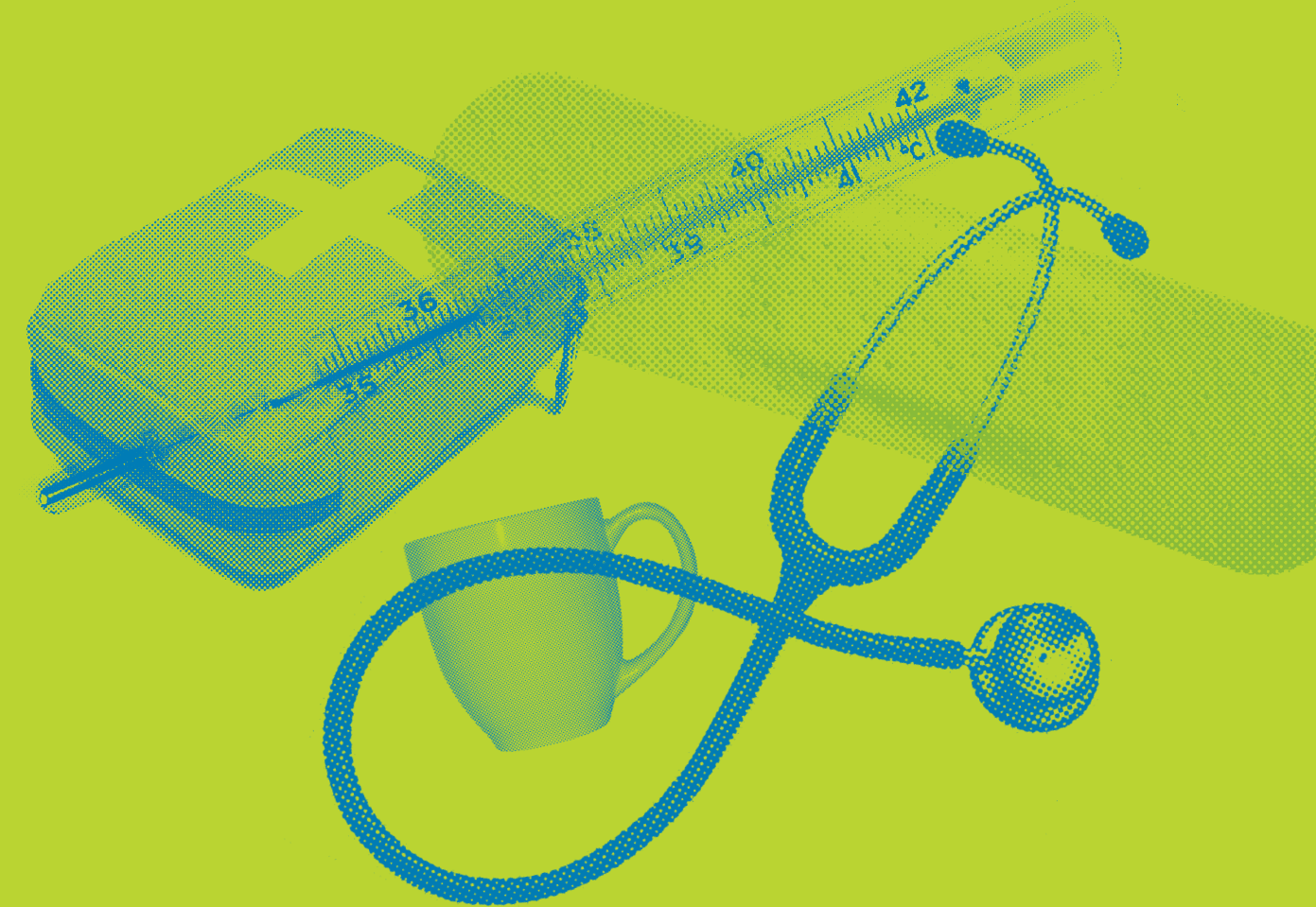
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# Homeless to Home Healthcare

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Micah Projects (07) 3029 7000  
healthcare@micahprojects.org.au  
www.micahprojects.org.au  
PO Box 3449, South Brisbane Q 4101

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