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# Cost Savings of Housing First in a Non-Experimental Setting

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Les auteurs analysent l'incidence des programmes de logement supervisé (programme Logement d'abord) sur le recours des personnes sans domicile aux services publics, à Calgary (Alberta). Ils utilisent les données relatives aux clients entre 2012 et 2016 et, procédant à un examen avant-après, ils évaluent l'interaction de chaque client avec les systèmes de santé et de justice. Selon leurs estimations, pour 1 \$ consacré au programme Logement d'abord, les économies se situent entre 1,17 \$ et 2,84 \$. Bien que des erreurs d'estimation soient possibles, leurs évaluations sont globalement conformes aux observations tirées d'essais aléatoires contrôlés. Les estimations de rendement quelque peu supérieures peuvent être attribuées aux modalités de livraison du programme et à l'efficacité du système de triage.

**Mots clés :** économies de coûts, itinérance, Logement d'abord, logement subventionné, soins de santé, système de justice

We investigate the impact of supportive housing (Housing First, or HF) programs on public service utilization of people experiencing homelessness in Calgary, Alberta. We use data on clients between 2012 and 2016, and, using a pre-post design, we assess the interaction of each client with the health and justice systems. We estimate the savings for \$1 spent on HF to be between \$1.17 and \$2.84. There are potential estimation biases, but our estimates are broadly consistent with evidence from randomized controlled trials. Our somewhat higher estimated returns may be attributed to the practice of program delivery and effectiveness of the triage system.

**Keywords:** homelessness, Housing First, subsidized housing, cost savings, health care, justice system

## Introduction

Housing First (HF) is a model that provides immediate access to affordable housing to address the needs of people experiencing homelessness; HF does not require abstaining from substance abuse or adhering to medical care plans (Goering et al. 2011; Tsemberis 2010). Once controversial, this approach is now popular across North America, in part because of experimental evidence from randomized controlled trials (RCTs) that the program can lead to lower utilization of publicly funded health and justice services, particularly for individuals with a mental health condition (Goering et al. 2014). HF represents a departure from earlier strategies to house people

experiencing chronic homelessness: previous housing strategies typically required participants to achieve sobriety or exhibit behavioural change before they were given their own dwelling (Tsemberis, Gulcur, and Nakae 2004).

Naturally, demonstrations of HF's higher rate of successfully housing those who are chronically homeless lead to questions regarding cost, centered on whether HF pays for itself through cost savings from other publicly funded systems. Studies differ on whether HF results in a net cost savings (Ly and Latimer 2015), and it is unclear what decision rules should be used to decide who should receive HF if cost saving is the goal, or whether cost savings should even be considered a goal (Katz, Zerger, and Hwang 2017).

Despite these concerns, HF delivery continues to evolve in Canada, and data on participant outcomes continue to accrue, so up-to-date estimates of potential cost savings to governments in different settings are useful for policy-makers and program planners.

Against this backdrop, our study presents evidence from actual utilization of HF programs in Calgary, taking advantage of a robust administrative dataset on HF programs. We study the net impact of a HF program with no formally mandated research design aspect; this is a study of the cost savings of HF in practice rather than of its ability to house chronically homeless individuals, which has been established. We seek to answer two questions: Did the delivery of HF reduce utilization of the health and legal systems? If so, by how much and over what period?

Our article is organized as follows: We first provide background for our study, including the context in which the HF intervention is deployed, the rise of HF programs, and estimates of their value. In the next section, we describe our data and statistical methods. Then we cover our results and conclude with a discussion of the results.

## Background

Homelessness grew substantially in Canada in the 1980s and 1990s, driven by both labour market changes and the reduction in generosity of various forms of social spending, including affordable housing and income assistance (Gaetz et al. 2016). Calgary in particular saw a very sharp rise in homelessness beginning in the mid-1990s; according to analysis done with Point-in-Time Count methodology, homelessness in Calgary grew by almost 700 percent between 1996 and 2008 (Calgary Homeless Foundation 2014).

In many cases, people who stay in an emergency shelter will regain shelter without substantial public resources. For example, they might find housing on their own; in other cases, family and friends may provide them with short-term assistance (e.g., some financial support, a couch to sleep on). These transitional shelter users make up a majority of shelter users in Calgary (Kneebone et al. 2015). Similar patterns of shelter use have been observed in New York City and Philadelphia (Kuhn and Culhane 1998) and in Toronto, Guelph, Ottawa, and Victoria (Aubry et al. 2013; Jadidzadeh and Kneebone 2018; Rabinovitch, Pauly, and Zhao 2016). A more significant challenge are those who are chronically homeless – those who stay in emergency shelters (and outdoors) for longer stretches of time with few interruptions (Kuhn and Culhane 1998). In Calgary, these individuals are estimated to use more than one-third of shelter bed resources, yet they make up less than 2 percent of the total shelter-using population (Kneebone et al. 2015).

Homelessness became a pressing public policy challenge in several of Canada's major cities beginning in the 1980s. Just as Canada's labour market started to struggle

with higher unemployment, senior orders of government were also cutting back on social spending, including on housing and income support programs (Suttor 2016). Across Canada, there was initially a range of uncoordinated policy responses to this rising homelessness; it was common for housing providers to require prospective tenants to demonstrate that they were not using drugs or alcohol ("clean and sober") and were following physician-directed treatment plans for any major mental health challenges (Suttor 2016). This housing readiness expectation began to change in Canada with the emergence of Toronto's large HF program (Streets to Homes) in 2005. Since that time, most advocates, researchers, and policy-makers have generally embraced the approach (Falvo 2009).

HF's rising popularity is partly due to experimental evidence showing that the majority of participants are able to maintain long-term housing (Stergiopoulos et al. 2015; Tsemberis et al. 2004). Program effectiveness has been established in the sense that individuals successfully graduate from the various programs into the private housing market, about 20% in the first year (Jadidzadeh and Falvo 2019).

Economic evaluations of the cost of HF programs and attributable costs avoided from other publicly funded systems (common examples are the health and justice systems) complement the results from RCTs and observational studies (Ly and Latimer 2015). The focus on the efficiency of HF has been criticized by some as inappropriately emphasizing the program's market value instead of its role in helping vulnerable individuals, not addressing the policy context within which HF operates, or not addressing the root causes of chronic homelessness (Katz et al. 2017; Willse 2010). Economic evaluations are one of many pieces of evidence used to present HF as an option for governments to take action on a social problem; however, it is not our contention that economic evaluations are the single analytic tool that justifies action. We summarize some key findings from this literature here.

One frequently cited academic study on the cost of homelessness in North America is Culhane, Metraux, and Hadley's 2002 study using data from New York City regarding individuals with serious mental health diagnoses placed in supportive housing. Placement into supportive housing was associated with an average reduction in service use of slightly more than US\$16,000 per housing unit per year (using nominal dollar values). Since the annual cost of the housing unit was just over US\$17,000, the net cost of each housing unit is estimated to be approximately US\$1,000 annually per housing unit over the course of the first two years.

The data in the Culhane et al. (2002) study cover 1989–1997, before widespread adoption of HF, and so that study represents one of the early proofs of the concept that housing a person with complex needs generates savings

that partially offset the cost of the housing. Innovations in the delivery of services to people experiencing homelessness (both during homelessness and after they receive permanent housing) other than HF have expanded since their study, meaning past costs do not predict current costs. For example, many North American cities—especially Calgary—have developed sophisticated systems to assess and triage clients, monitor program performance, and provide highly targeted (and often time-limited) interventions (Clarkson et al. 2017; Li et al. 2017).

Observational evidence on the potential cost savings of HF is underdeveloped for Canada. To our knowledge, the peer-reviewed literature includes are no studies using observational data of HF programs from Canada. Several American studies have used observational data and a pre-post design, and according to a systematic review (Ly and Latimer 2015), studies of that type tend to show cost savings.

For example, a study of HF participants in California found that found increased outpatient costs for HF participants were more than offset by decreased inpatient and emergency costs, but total program costs were higher than savings for two years of follow-up (Gilmer, Manning, and Ettner 2009). A study of chronically homeless individuals in Seattle with severe alcohol-related problems found a net savings of US\$2,449 per participant per month, with HF participants experiencing a large decrease in costs (53%) during their first six months in the program (Larimer et al. 2009). Another Washington State study identified that a small sample of high-service users experienced a substantial drop in health and justice system utilization on becoming housed compared with a control group, offsetting twice the cost of the intervention (Srebniak, Connor, and Sylla 2013). These findings indicate that the cost savings of HF can be immediate and substantial and might be variable depending on the needs of participants.

US cost-benefit analyses of housing that take into account health and justice services utilization do not generalize to Canada because of the different health care and justice systems and associated lower health costs in Canada (Anderson et al. 2003). Thus, we focus on the Canadian literature regarding HF.

The largest HF experiment in Canada, the At Home/ Chez Soi program, followed 2,148 people across five sites for two years: Vancouver, Winnipeg, Toronto, Montreal, and Moncton. A cost evaluation component accompanied the RCT. When considering only those in the top decile of public services use, HF was a substantial cost saver: \$1 invested in HF saved approximately \$2.17 in health and justice services such as hospital stays, emergency room (ER) visits, police contacts, or prison stays (Goering et al. 2014). Across all study participants, however, HF resulted in no net savings despite substantial offsets (especially for the high-needs participants); the study points to the short follow-up period as a potential influence. Other analyses of the same data focused on the mode of HF delivery are

consistent, with estimates of the cost offset from public services at 96 percent of the cost of the program depending on the needs of participants (Aubry et al. 2016).

Our objective is to study the impacts of HF programs when a large central homeless-serving organization (i.e., a system planner) provides program oversight—in other words, HF applied on a large scale to a real population of homeless people. We use longitudinal individual-level data on health and justice system utilization to observe costs to public systems before and after joining HF and cost data from the HF program to estimate cost offsets or savings associated with HF. In Calgary, participants are triaged into HF on the basis of perceived need, meaning we can estimate whether HF is cost saving for those who participate. Moreover, with the large dataset described next, we have enough participants to estimate accurate changes in service use.

## Methods

### Data Sources

The Calgary Homeless Foundation (CHF) collects information on HF participants using a standardized form at move-in and quarterly follow-up assessments. The quarterly assessments contain information about utilization of the health and justice systems for the previous three months; the move-in assessment gathers the same information for the previous 12 months. Further information and the forms themselves can be found at <http://calgary-homeless.com/agencies/hmis/user-information-tools/>.

In the present context, HF is not a single program; rather, it is an approach to housing people used by a collection of programs delivered by different service providers in the city. The programs each have different aspects (e.g., some house all participants in the same building, and others scatter participants across many sites), but they are all HF programs in the sense that there is no sobriety or other qualifications for housing assignment. We use data for all single individual program participants (no family or youth program participants) across 25 distinct programs delivered by 11 different agencies.

We have access to data from the fiscal year starting April 2012 through the fiscal year ending March 2017 (i.e., five years of HF data). We can observe the date on which participants begins the program and the date on which they leave. Because HF is voluntary, participants can exit whenever they wish (however, for time-limited programs, participants are encouraged to move on to more independent housing). The variables we use in this study to represent health and justice system utilization (our outcome variables) are number of hospital visits, number of ER visits, and number of interactions with police. All variables are self-reported by participants but recorded by a case manager who typically has some familiarity with participants, allowing for some vetting of responses.

Individuals in the sample were triaged to HF programs largely on the basis of their level of need—a function of their health, past trauma, vulnerability, service use, life skills, and housing history. This is determined by the Service Prioritization Decision Assessment Tool (SPDAT; more information and the forms can be found at the link provided earlier<sup>1</sup>). Individuals are not randomly assigned to their HF program; that decision is made by a committee consisting of HF program managers and CHF staff on the basis of individual needs and housing availability.

Costing data for hospital and ER visits are available from the provincial government’s Ministry of Health (Alberta Health), which publishes reports on the cost of providing both of these services for people experiencing homelessness. Per-person hospital stays for homeless individuals are longer than for the general population; individuals experiencing homelessness tend to have more intense health problems (Hwang 2001). Alberta Health estimates that a single hospital visit for someone experiencing homelessness is \$18,100, approximately \$2,600 more than a member of the general population (Alberta Health 2018b). ER visits are estimated to cost \$830, approximately \$230 more than for the general population (Alberta Health 2018a). We use these dollar values as the unit cost for a single visit of either type.

Costing data for Calgary Police Services are difficult to itemize because an interaction with police can potentially lead to imprisonment and other systems use. Therefore,

we use the estimated cost of the warrant cycle as the average cost of an interaction with police. Figure 1 shows the warrant cycle. Briefly, issuing a ticket costs \$139, and arresting an individual who has not paid a ticket costs an additional \$135. The cost of the resultant court appearance ranges between \$222 and \$253. An individual can have more than one outstanding ticket at a time because the warrant cycle takes time to move to the next stage. If an individual is convicted, then one day in jail costs \$220. Each warrant cycle is estimated to cost a total of \$1,376, which we use as the unit cost for a single interaction with police.

**Data Structure**

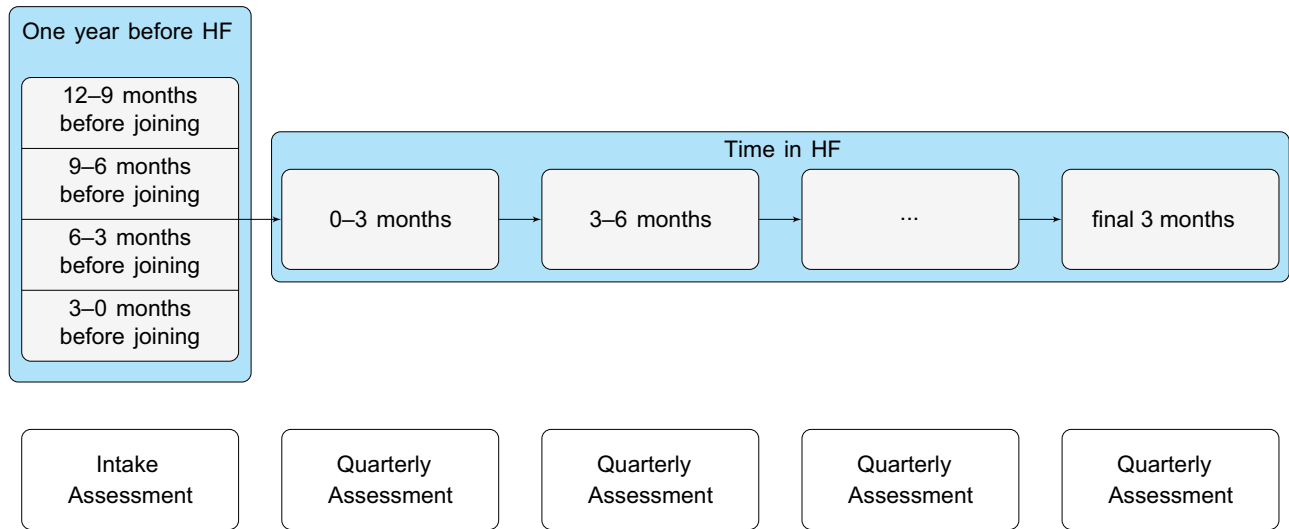
On entry to HF, an individual completes a move-in assessment survey that includes information on the past year’s utilization of health and justice services. The utilization questions at move-in are identical to those gathered during quarterly assessments, other than the different time ranges. To compare quarterly assessments (every three months) with move-in assessments (previous 12 months), we divide utilization reported at move-in by four, which we refer to as pre-HF utilization or baseline utilization. The resultant dataset contains utilization for every three months and baseline utilization (utilization three months before joining). Each three-month block is comparable to the baseline utilization period and reflects an equal amount of time for consumption of services, shown in Figure 2.



**Figure 1:** Cost of Warrant Incarceration Cycle in Calgary

Notes: CSS = Court Services Section; FTA = fail to appear; PTA = promise to appear.

Source: Calgary Police Service.



**Figure 2:** Data Gathering Process

Notes: Each assessment concerns system utilization only within the pertaining time period. System utilization during the intake assessment covers the previous year. We divide reported values by four to estimate quarterly use. HF = Housing First.

Source: Authors.

Overall, our dataset contains 2,222 individuals. To arrive at this number, we excluded 562 individuals from the 2,784 total HF enrollees who provide no follow-up assessments. Individuals who never used the health and justice services that we modeled were dropped from our analytical sample because the model we chose would ignore those observations (we account for this later). The number of eligible individuals for each outcome variable is 1,147 for hospital visits, 1,130 for ER visits, and 988 for police interactions.

Table 1 shows the annual cost per client, excluding capital costs, for five broadly defined program types

**Table 1:** Annual Cost per Client in Different Housing Types in Single Adult Sector

Program Types	Cost/Client, \$
Assertive community treatment	25,936
• Clients with the very highest levels of need	
• No time limit	
Permanent supportive housing, high need	30,528
• No time limit	
Supportive housing, high need	16,847
• Time limited	
Supportive housing, medium need	13,930
• Time limited	
Transitional housing	20,030
• Time limited	
• Client's experience with homelessness has been relatively limited	

Source: Calgary Homeless Foundation.

covering 25 different individual programs and contrasts them. Briefly, assertive community treatment is a team-based approach designed to provide comprehensive community-based supports. These teams may consist of physicians and other health care providers, social workers, and peer support workers. Permanent supportive housing (PSH) provides long-term housing and support with no time limit for high-need individuals experiencing major barriers and exhibiting complex needs and who will require ongoing support to maintain their housing. Supportive housing provides case management and housing supports to individuals and families who are considered mid- to high need. In this program type, the goal is that over time and with case management support, the client will be able to achieve housing stability and independence (i.e., no further need for case management support). Transitional housing is an intermediate step between emergency shelter and permanent housing. It is more long-term, service-intensive, and private than an emergency shelter, yet remains time-limited. Annual costs for a client in HF can range from \$13,930 to \$30,528 depending on program type.

**Cost Savings Estimation Strategy**

Our outcome variables are count variables, that is, the distributions are positively skewed, have a minimum of zero, and contain many zero observations. Appropriate models for count data are models that acknowledge the natural floor of the data at zero and can account for excessive zeroes (Cameron and Trivedi 2009). We estimate two different models of utilization over time in HF programs: (1) fixed-effects ordinary least squares (OLS) models,

which estimate average changes in utilization but are not specific to count data, and (2) fixed-effects negative binomial models, which estimate changes in the incidence rate of utilization and are specifically designed for count data. We compare and interpret the results from both models.

Using both types of model, we model the effect of time in HF on utilization of our outcome variables through dummy variables for each quarterly follow-up assessment (every three months) and interpret decreases over time versus baseline as the impact of program participation on utilization. Our regression models are as follows:

$$\text{Utilization}_{it} = \beta_0 + \sum_{t=1}^{12} \beta_t \text{Quarter}_t + \mu_{it},$$

where we have  $t$  quarters, up to a possible 12, for the four years of follow-up we allow per individual. We model the quarters as dummy variables, with baseline utilization captured by the constant. In the OLS fixed-effects model, the error term is broken out into two terms: one that captures the individual-specific, time-invariant factors that correlate with utilization,  $\alpha_{it}$ , and a term for random noise,  $e_{it}$ .

The coefficients for the quarters, the  $\beta_t$  terms, represent the difference between utilization in the quarter versus baseline. That means the coefficient, when measured in units in the OLS regression, is the marginal effect on utilization. In the negative binomial model, we report the coefficients as incidence rate ratios: the number of visits in the quarterly report divided by the number of visits in the baseline quarter. To establish the marginal effect on utilization, we multiply this coefficient by baseline utilization in units to solve for quarterly utilization in units. The advantage over OLS is that this incidence rate is calculated by a model that accounts for the high number of zeroes in count data. All models were run in Stata 14.2 (StataCorp, College Station, TX).

After the regression analysis, we conduct a costing analysis in which we estimate the cost savings from the program for system use by multiplying average costs reported earlier by the marginal effect provided by the regression models. We then provide deflated estimates in which we spread the estimated benefits over the entire sample of HF users, including those excluded from the models.

## Results

Table 2 shows participant demographics. The three samples are qualitatively similar to one another. Those providing information for police interactions are more likely to be young adults aged 25–44 years, more likely to be in high-need supportive housing, and less likely to be Caucasian. More than 50 percent of the sample who interacted with any of the systems were placed in

a high-need program, and nearly all participants in the sample are Canadian citizens. Table 3 shows summary statistics for our three outcome variables. The high number of zero-count observations supports the use of a negative binomial model.

Tables 4–6 show the regression results and time-specific sample sizes. The negative binomial coefficients are exponentiated so they are interpretable as incidence rate ratios (IRRs). For example, a coefficient of 0.45 for the variable 3 months indicates that the incidence rate during the first three months in HF was approximately 45 percent of the incidence rate at baseline, or a 55 percent decrease in utilization from baseline. The least squares coefficients are reported in natural units, so a coefficient of  $-0.42$  for the variable 3 months indicates the average decrease in utilization was 0.42 units (e.g., hospital visits). The estimates of effect across models for hospital visits are statistically significant across all quarters and indicate decreases in hospital use. The coefficients indicating reductions in emergency visits are statistically significant for about two years. This is likely the result of the size of the estimated effectiveness decreasing over time. The coefficients indicating reduced police interactions are statistically significant for all four years, with the exception of the last period in the case of the negative binomial model. In all models, the estimated magnitudes are somewhat consistent over time, meaning the initial decreases on joining HF persist with slight variation. The models produce slightly different results because negative binomial regression acknowledges the left censoring and discrete nature of count data.

For hospital visits, the IRRs indicate a decrease in utilization by 55 percent on entering HF. Using Table 2's values, average utilization went from 0.95 visits to 0.43 visits and remained at approximately that level for four years of follow-up. Baseline levels of 0.91 ER visits per person decreased to a minimum of 0.62 per person at 21 months. For police interactions, the baseline level of 3.45 per person decreased to 2.31 and remained at approximately that level for four years of follow-up.

The least-squares models indicate similar-magnitude decreases. For hospital visits, we observe a decrease of 0.53 visits that persists for four years with mild variation; ER visits fluctuation between 0.05 and 0.25 fewer visits; and there are approximately 2 fewer police encounters. The differences between the negative binomial models and least squares models are not uniform; the effect on police times is higher in the least squares model, but the effect on ER visits is higher in the negative binomial model.

We then estimate the cost savings of the HF program by multiplying the estimated point decrease in utilization, whether it is statistically significant or not, by the average cost of the services for each three-month period (Table 7). The estimated savings over four years are \$213,243.53

**Table 2:** Participant Demographics on Move-In Date

Characteristic	n (%) <sup>a</sup>		
	Hospital Visits	Emergency Room Visits	Police Interactions <sup>b</sup>
No. of unique IDs	1,147	1,130	988
Gender			
Male	753 (66)	717 (63)	645 (65)
Female	394 (34)	413 (37)	343 (35)
Ethnicity			
Caucasian	745 (65)	721 (64)	577 (58)
Aboriginal	295 (26)	310 (27)	315 (32)
Other	107 (9)	99 (9)	96 (10)
Immigration			
Canadian citizen	1,103 (96)	1,094 (97)	958 (97)
Permanent resident	43 (4)	33 (3)	27 (3)
Other	1 (0)	3 (0)	3 (0)
Age, years			
18–24 (youth)	60 (5)	58 (5)	56 (6)
25–44 (young adult)	464 (40)	461 (41)	492 (50)
45–59 (middle age)	544 (47)	541 (48)	409 (41)
≥ 60 (senior)	79 (7)	70 (6)	31 (3)
Program type			
Assertive community treatment	126 (11)	107 (9)	105 (11)
Permanent supportive housing, high need	160 (14)	153 (14)	116 (12)
Supportive housing, high need	410 (36)	418 (37)	418 (42)
Supportive housing, medium level of need	398 (35)	384 (34)	309 (31)
Transitional housing	53 (5)	68 (6)	40 (4)
Baseline average utilization, mean (SD)	0.95 (1.94)	0.91 (2.41)	3.45 (12.74)

Note: Percentages may not total 100 because of rounding. IDs = identifications.

<sup>a</sup> Unless otherwise indicated.

<sup>b</sup> Participants could have more than one interaction.

Source: Authors.

**Table 3:** Summary Statistics for Outcome Measures at Baseline and After Three Months in Program

Statistic	Hospital Visits		Emergency Room Visits		Police Interactions	
	Baseline	First 3 Months	Baseline	First 3 Months	Baseline	First 3 Months
Mean	0.95	0.53	0.91	0.75	2.19	0.87
SD	1.94	1.45	2.41	1.66	10.83	4.81
% of observations that are 0	34	72	58	62	82	88
n	1,147	1,147	1,130	1,130	988	988

Source: Authors.

using the negative binomial model and \$197,086.36 using OLS; the annual average cost savings are \$53,310.88 and \$49,271.59, respectively.

The costs of HF are averaged across program utilization of all observed participants because we are estimating systems-level impacts. On the basis of the slightly different distributions of program type across our three samples, we calculate the average of the total weighted cost estimates of

HF per person-year (Table 8). We estimate that the average individual in the sample used approximately \$18,761.61 of HF services in any year.

The ratio of the annual average cost savings (Table 7) to the total weighted cost estimates per person-year (Table 8) is the dollars saved from health and justice per dollar spent on HF. For both regression models, the value of the savings or costs is greater than 2.5, meaning \$1 spent



**Table 4:** Negative Binomial and Least Squares Fixed Effect Estimates: Hospital Visits

Hospital Visits, Months	Negative Binomial Fixed Effect <sup>a</sup>			Least Squares Fixed Effect <sup>b</sup>			n
	Coefficient	SE	p >  z	Coefficient	SE	p >  z	
3	0.450	0.029	0.000	-0.424	0.047	0.000	1,147
6	0.392	0.028	0.000	-0.529	0.050	0.000	1,005
9	0.364	0.030	0.000	-0.520	0.052	0.000	867
12	0.364	0.032	0.000	-0.531	0.055	0.000	735
15	0.360	0.036	0.000	-0.519	0.059	0.000	609
18	0.344	0.039	0.000	-0.515	0.063	0.000	509
21	0.358	0.044	0.000	-0.517	0.067	0.000	430
24	0.379	0.050	0.000	-0.501	0.072	0.000	361
27	0.405	0.057	0.000	-0.475	0.076	0.000	310
30	0.290	0.051	0.000	-0.545	0.080	0.000	274
33	0.442	0.072	0.000	-0.406	0.086	0.000	232
36	0.403	0.077	0.000	-0.481	0.095	0.000	181
39	0.470	0.092	0.000	-0.441	0.104	0.000	146
42	0.385	0.092	0.000	-0.490	0.114	0.000	118
45	0.218	0.083	0.000	-0.541	0.130	0.000	88
48	0.257	0.106	0.001	-0.526	0.151	0.000	64
Intercept	1.700	0.125	0.000	0.864	0.035	0.000	1,147
n		8,223			8,223		

<sup>a</sup> The coefficients for the negative binomial model are exponentiated so they are interpretable as incidence rate ratios (IRRs), with a number < 1 indicating a decrease in use. An IRR indicates use relative to baseline; for example, a coefficient of 0.45 for the variable 3 months indicates that the incidence rate during the first three months in HF was approximately 45 percent of the incidence rate at baseline. Statistical significance is calculated for the null hypothesis that the coefficient is equal to 1.

<sup>b</sup> In the least squares model, the coefficients are interpreted as the time-period-specific change in use versus the baseline, with a number < 0 indicating a decrease in use. For example, a coefficient of -0.424 for the variable 3 months indicates that respondents used, on average, 0.424 fewer hospital visits in their first three months of housing first. Statistical significance is calculated for the null hypothesis that the coefficient is equal to 0.

Source: Authors.

on HF is associated with more than \$2.50 of savings to the public system (Table 9).

Not all individuals in the HF programs use the health and justice outcomes we track. Our smallest estimation sample, 988 people, is only a fraction of the 2,222 HF singles in our dataset. Because we only observe systems utilization decreases for that 44.5 percent of participants, we deflate the cost savings by 0.445 to provide an estimate of cost savings for the entire HF program. That means we are assuming no savings for the remaining 55.5 percent of HF participants. With this deflation we observe an estimated \$1.26 to \$1.17 in savings for \$1 spent on HF.

## Discussion

Our study is the first large, observational, longitudinal evaluation of cost savings to the public system associated with an HF program coordinated by a system planner in Canada. We estimate that the savings of HF as coordinated by CHF, the system planner, and delivered by many smaller programs can be substantial. Our estimates represent the net impact of the HF programs and the triage

process that selects participants into HF. Saving greater than \$2.50 for each \$1 spent on HF means, with proper prioritization of participants, the approximately \$42 million budgeted on HF for fiscal year 2018–19 could result in savings of more than \$105 million in terms of hospital visits, ER visits, and justice services. Even if we deflate the benefits and assume those not in our models experienced no benefit in terms of systems utilization, we still observe complete cost offsets. We do not include emergency shelter utilization as a cost saving because we could not estimate how many shelter stays participants would have used had they not been in HF, but each year of shelter use avoided represents an additional \$12,240 in savings.

This result is important for informing HF delivery, especially in Canada. First, it supports experimental evidence that shows that HF improves long-run housing stability for participants and can have significant cost offsets. Although analyses of the AHCS study (Aubry et al. 2016; Goering et al. 2014) indicate the program works, no other published data outside of that experiment matches the sample size or length of follow-up in Canada used

**Table 5:** Negative Binomial and Least Squares Fixed Effect Estimates: Emergency Room Visits

ER Visits, Months	Negative Binomial Fixed Effect <sup>a</sup>			Least Squares Fixed Effect <sup>b</sup>			n
	Coefficient	SE	p >  z	Coefficient	SE	p >  z	
3	0.879	0.056	0.042	-0.164	0.060	0.006	1,130
6	0.850	0.058	0.018	-0.168	0.063	0.008	1,002
9	0.818	0.062	0.008	-0.187	0.066	0.005	868
12	0.729	0.062	0.000	-0.235	0.070	0.001	740
15	0.750	0.068	0.001	-0.226	0.074	0.002	624
18	0.720	0.074	0.001	-0.225	0.079	0.004	516
21	0.686	0.079	0.001	-0.219	0.084	0.009	443
24	0.776	0.096	0.040	-0.169	0.089	0.059	371
27	0.901	0.116	0.418	-0.041	0.096	0.668	308
30	0.694	0.104	0.015	-0.224	0.101	0.027	270
33	0.981	0.143	0.895	-0.077	0.108	0.479	228
36	1.019	0.167	0.909	-0.043	0.120	0.717	179
39	0.824	0.158	0.312	-0.181	0.131	0.165	147
42	0.839	0.181	0.415	-0.155	0.143	0.278	120
45	1.058	0.246	0.808	-0.077	0.163	0.637	89
48	0.877	0.253	0.650	-0.121	0.187	0.518	66
Intercept	0.901	0.065	0.148	0.747	0.044	0.000	1,130
n		8,231			8,231		

Note: ER = emergency room.

<sup>a</sup> The coefficients for the negative binomial model are exponentiated so they are interpretable as incidence rate ratios (IRRs), with a number < 1 indicating a decrease in use. An IRR indicates use relative to baseline; for example, a coefficient of 0.45 for the variable 3 months indicates that the incidence rate during the first three months in HF was approximately 45 percent of the incidence rate at baseline. Statistical significance is calculated for the null hypothesis that the coefficient is equal to 1.

<sup>b</sup> In the least squares model, the coefficients are interpreted as the time-period-specific change in use versus the baseline, with a number < 0 indicating a decrease in use. For example, a coefficient of -0.424 for the variable 3 months indicates that respondents used, on average, 0.424 fewer hospital visits in their first three months of housing first. Statistical significance is calculated for the null hypothesis that the coefficient is equal to 0.

Source: Authors.

in our current study. The question of whether an organization with no mandated experimental design aspect to program delivery, a standardized follow-up assessment program, and real-world cost pressures can deliver savings to other publicly funded systems has been resolved with our findings.

Second, our result shows that the triage and prioritization processes developed by organizations delivering HF result in larger returns to investment than the experimental evidence suggests. There are returns to following best practices established in other jurisdictions, but it is also possible that other jurisdictions will not experience similar cost offsets. Our sample has lower average baseline health services utilization than a large sample of people experiencing homelessness in Toronto (Hwang et al. 2013), implying that city-specific considerations are important when discussing the feasibility of HF. In other words, if the Calgary participants in HF use fewer health care services, we could expect them to contribute lower savings than in Toronto. Although our current

study shows significant cost offsets, that need not be true across Canada.

Moreover, our study shows that the cost savings of HF programs are a function of the client mix. The average of our estimates of cost savings to program total cost invested (Table 9) is 2.73, meaning that for the entire program to pay for itself, we estimate that 1/2.73, or about 37%, of the participants need to experience a decrease in system utilization typical of those observed in our study. Therefore, other Canadian cities might not expect to see cost savings in reduced services if HF recipients do not have the same system utilization pattern. Consequently, HF might not be the most appropriate tool for all jurisdictions.

When considering evidence from the United States, numerous other studies have contributed estimates of net cost savings of HF, and the results are mixed. One important consideration is study design. A systematic review of supportive housing cost savings analyses suggests that experimental studies are less likely to show net cost savings than pre-post design studies except in the most chronic

**Table 6:** Negative Binomial and Least Squares Fixed Effect Estimates: Police Interactions

Police Interactions, Months	Negative Binomial Fixed Effect <sup>a</sup>			Least Squares Fixed Effect <sup>b</sup>			n
	Coefficient	SE	p >  z	Coefficient	SE	p >  z	
3	0.671	0.045	0.000	-2.147	0.224	0.000	988
6	0.628	0.046	0.000	-2.150	0.235	0.000	866
9	0.662	0.051	0.000	-2.174	0.247	0.000	753
12	0.601	0.051	0.000	-2.246	0.259	0.000	656
15	0.539	0.051	0.000	-2.370	0.273	0.000	560
18	0.467	0.051	0.000	-2.478	0.291	0.000	469
21	0.538	0.061	0.000	-2.323	0.308	0.000	400
24	0.549	0.069	0.000	-2.247	0.330	0.000	333
27	0.466	0.067	0.000	-2.356	0.352	0.000	283
30	0.473	0.072	0.000	-2.415	0.375	0.000	240
33	0.480	0.080	0.000	-2.322	0.400	0.000	205
36	0.392	0.083	0.000	-2.305	0.452	0.000	153
39	0.279	0.079	0.000	-2.349	0.516	0.000	113
42	0.413	0.106	0.001	-2.360	0.571	0.000	90
45	0.368	0.113	0.001	-2.398	0.636	0.000	71
48	0.632	0.167	0.083	-2.375	0.709	0.001	56
Intercept	0.579	0.037	0.000	3.153	0.166	0.000	988
N		7,224			7,224		

<sup>a</sup> The coefficients for the negative binomial model are exponentiated so they are interpretable as incidence rate ratios (IRRs), with a number < 1 indicating a decrease in use. An IRR indicates use relative to baseline; for example, a coefficient of 0.45 for the variable 3 months indicates that the incidence rate during the first three months in HF was approximately 45 percent of the incidence rate at baseline. Statistical significance is calculated for the null hypothesis that the coefficient is equal to 1.

<sup>b</sup> In the least squares model, the coefficients are interpreted as the time-period-specific change in use versus the baseline, with a number < 0 indicating a decrease in use. For example, a coefficient of -0.424 for the variable 3 months indicates that respondents used, on average, 0.424 fewer hospital visits in their first three months of housing first. Statistical significance is calculated for the null hypothesis that the coefficient is equal to 0.

Source: Authors.

groups (e.g., those with mental health conditions, those with heavy system utilization; Ly and Latimer 2015). We suggest that this can partially be attributed to regression to the mean levels of utilization by participants who were in a crisis state before entering these programs. Regression to the mean is a potential source of estimation bias here as well: some HF participants who were chosen because of high need may well have reduced their interactions with the health and justice systems without HF. As noted, however, our estimates are not wildly higher than those of the Canadian AHCS trial. Our cost-savings-to-program-total cost ratio estimate is 2.73 for those with pre-program health or justice interaction compared with the ACHS top-decile estimate of 2.17, and our all-participant minimum ratio estimate is 1.17 compared with the ACHS estimate of 0.96. Although our higher estimates could in part be due to regression to the mean, they could also be higher because our evaluation of HF in practice acknowledges that assignment to HF is non-random, much as hospital care is not randomly assigned to all citizens who engage with the health care system. Like any program involving

triage, the need of those accessing HF in part determines the return to public systems and that average level of need could vary by city. A concrete example would be that the average level of need in a large city might be higher than in a nearby suburb. Continued evaluation of HF is required to determine whether HF remains an efficient form of housing support with either program scale-up or innovations in delivery. HF is not one program, nor are estimates of the benefits of HF generalizable to all cities, so it follows that cost savings estimates at a systems level are also city specific.

The issue of study design is an important one: if experimental evidence exists to show HF can be cost saving for heavy system users, then why bother with a less rigorous research design using observational data? There are two broad reasons. First, observational data confront the issue of whether something works under experimental conditions or works in practice (Drummond et al. 2005). The experimental design measures the effect of assigning a random individual to a HF program, that is, whether HF can possibly result in cost savings. In Calgary, individuals

**Table 7:** Cost Savings in Dollars per Time Period (Quarter) by Regression Technique and Service

Time Period, Months	Negative Binomial Regression				Least Squares Regression			
	Hospital Visits	ER Times	Police Times	Total	Hospital Visits	ER Times	Police Times	Total
3	9,465.11	91.33	1,562.36	11,118.79	7,669.22	135.88	2,953.94	10,759.05
6	10,458.29	113.32	1,766.08	12,337.70	9,579.79	139.18	2,957.84	12,676.81
9	10,933.52	137.45	1,606.29	12,677.26	9,403.07	154.80	2,990.87	12,548.74
12	10,934.94	204.92	1,893.34	13,033.20	9,618.12	194.95	3,089.86	12,902.93
15	11,003.60	188.92	2,189.84	13,382.36	9,393.94	187.48	3,261.45	12,842.87
18	11,288.65	211.53	2,532.31	14,032.49	9,317.57	186.86	3,409.29	12,913.72
21	11,036.20	236.99	2,194.07	13,467.25	9,357.85	182.08	3,196.43	12,736.37
24	10,683.55	169.10	2,141.01	12,993.66	9,064.02	140.38	3,091.96	12,296.36
27	10,232.62	74.64	2,535.97	12,843.23	8,590.61	34.26	3,241.34	11,866.21
30	12,214.13	231.15	2,501.45	14,946.72	9,857.49	186.31	3,322.68	13,366.48
33	9,600.18	14.41	2,470.04	12,084.64	7,357.21	63.75	3,195.18	10,616.14
36	10,269.29	-14.21	2,884.49	13,139.57	8,709.07	36.07	3,171.37	11,916.51
39	9,122.96	132.94	3,424.27	12,680.17	7,977.15	150.63	3,231.56	11,359.33
42	10,580.87	121.88	2,785.52	13,488.27	8,869.87	128.54	3,246.84	12,245.25
45	13,446.82	-43.85	2,998.45	16,401.42	9,784.86	64.04	3,299.76	13,148.66
48	12,777.02	92.68	1,747.10	14,616.81	9,522.94	100.50	3,267.49	12,890.92
Total overall	174,047.74	1,963.19	37,232.60	213,243.53	144,072.79	2,085.72	50,927.85	197,086.36
Annual average cost savings				53,310.88				49,271.59

Note: ER = emergency room.

Source: Authors.

are assigned to HF programs on the basis of their needs. The intervention is more efficiently designed than a trial by design because resources are scarce—in other words, the expert-level decisions made by front-line staff and system planners in tandem could result in higher cost savings than are estimated from random assignment.

Second, HF is part of a system of social programs and policies operating on individuals. Commentators have suggested that uncritically privileging HF as an effective intervention ignores the system-level factors at play in generating homelessness and ignores the role played by proximal policy initiatives (e.g., the preventive role played by the generosity of available income supports; Katz et al. 2017). The experimental approach identifies that it is indeed possible for HF to deliver cost offsets or cost savings in a controlled setting. However, the actual implementation of HF (and resultant observational data) is informative in the presence of experimental evidence, especially because homelessness risk and risk factors can vary by city (Dutton and Jadidzadeh 2019). HF would not be expected to end homelessness because it does not address the root causes of chronic homelessness, and not all shelter users in a city are candidates for HF programs. In short, the policy context within which HF is delivered probably matters, and there is no guarantee HF will have a similar impact in all jurisdictions, nor that an expansion of HF in Calgary would have as large an impact on the

margin as we estimate for the existing program. The literature as a whole suggests that HF programs can offset costs, and possibly save costs, compared with emergency shelters (Ly and Latimer 2015), but Canadian research is lacking.

A limitation to our study is the reliance on self-reported utilization data. Self-reported responses to the survey tool provided during HF tenure are typically vetted by a caseworker who administers the survey tool; anecdotally, some caseworkers have claimed they are so familiar with the client they could fill out the quarterly assessments without the client present. Although there is no clear incentive for the client or caseworker to report system utilization in either direction, it is possible that caseworkers advocate for their clients to stay in HF programs and introduce measurement error into the study. The study could also be susceptible to recall bias: the baseline utilization data are gathered at intake to HF and based on one-year recall. Evidence suggests people who would be the target of HF programs (e.g., those experiencing chronic homelessness and those who are mentally ill) have reliable self-reported health and justice system utilization data (Somers et al. 2016).

Our study does not take into account the costs of capital associated with HF programs, which can be substantial. We evaluated the average savings to public systems attributable to an individual who participates in HF. In

**Table 8:** Weighted Average of Program Costs

Program Type	Average Cost per Person-Year, \$	Proportion of Sample by Outcome Variable			Weighted Cost per Person-Year, \$		
		Hospital Visits Sample	ER Visits Sample	Police Interactions Sample	Hospital Visits Sample	ER Visits Sample	Police Interactions Sample
Assertive Community Treatment	25,936	11	9	11	2,849.12	2,455.89	2,756.36
Permanent supportive housing, high need	30,528	14	14	12	4,258.48	4,133.44	3,584.26
Supportive housing, high need	16,847	36	37	42	6,022.03	6,231.90	7,127.58
Supportive housing, medium need	13,930	35	34	31	4,833.60	4,733.73	4,356.65
Transitional housing	20,030	5	6	4	925.54	1,205.35	810.93
Total weighted cost per person-year					18,888.77	18,760.30	18,635.77
Average of total weighted cost per person-year							18,761.61

Note: ER = emergency room.

Source: Authors.

**Table 9:** Cost Savings to Program Total Cost Ratios by Regression Model

Cost Savings	Negative Binomial Regression	Least Squares Regression
Annual average cost savings (Table 7), \$	53,310.88	49,271.59
Average of total weighted cost per person-year (Table 8)	18,761.61	18,761.61
Cost savings to program total cost ratio	2.84	2.63
Deflation factor <sup>a</sup>	0.445	0.445
Deflated cost savings to program total cost ratio	1.26	1.17

<sup>a</sup> The deflation factor is the proportion of the overall sample (2,222) in our smallest estimation sample (988). We observe system utilization for approximately 44.5% of total HF participants, so we assume the cost savings for the remainder of the participants is \$0 when we deflate our estimates.

Source: Authors.

particular, we focused on the efficiency of HF through variable costs—that is, costs that depend on utilization of the program. Some models of HF require fixed costs, such as the purchase of land or a building by the government, as does a hospital or a jail. These fixed costs are accounted for when establishing the budget impact of a program. This study is not a budget impact assessment; we used variable costs to evaluate the efficiency of HF delivery.

Our study does not observe the true system costs of the individuals in HF; rather, we estimate their costs

on the basis of average costs and utilization patterns. Future research would benefit from tracking the costs and types of service utilization through linked data. An important question is whether the type of care individuals require from the health care system or the nature of their interactions with the justice system change while in HF. Similarly, we make no effort to estimate the benefits to individuals enrolled in HF, for whom the benefits to successful addiction and mental health management are enormous, and who might experience

quality of life improvements in the future such as sustained employment.

Our sample size decreases over time as a result of attrition from various sources: individuals can graduate from HF (a positive outcome, meaning they move onto the private housing market), fail HF (meaning they are evicted or leave and are lost to follow-up), or re-enter the shelter-using group. Some of the programs are time limited and therefore graduate participants before our follow-up window closes. Our estimates pertain to those in HF during each time period, and the costs and cost savings are averaged over the entire group, despite the fact that those who leave might be different from those who remained in programs that allowed five years of follow-up. When we estimate costs, we treat participants as though they are contributing full costs over the entire time period whether they dropped out or not.

The systems-level savings estimated here will accrue mostly to the province, which funds the health system and courts, and to the municipal government that funds the police services. Funding for the HF programs comes mostly from the province with a substantial proportion coming from the federal government. Thus, the systems-level savings generated by HF programs are potentially vulnerable to the “wrong pocket” problem, a situation in which observed benefits are attributed to, or accumulate to, the wrong system (e.g., fewer health care costs, according to our analysis here, have little to do with the health care system; Taylor et al. 2016). Funding decisions are necessarily intertwined; for example, health outcomes depend on both health and social services spending (Dutton et al. 2018). Social spending on programs such as HF is a high-return substitute for health spending, and we show sizable cost offsets to health. Cuts to social spending programs such as HF will result in greater health spending to fund the consequent increase in hospital and ER utilization. HF is an example of a program that could be a target for redistribution from health to social spending portfolios, because the savings accrue to the same level of government.

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## References

- Alberta Health. 2018a. *Health Trends Alberta: Cost of Emergency Department Visits by Homeless Status*. Edmonton: Alberta Health.
- Alberta Health. 2018b. *Health Trends Alberta: Cost of Inpatient Stays by Homeless Status*. Edmonton: Alberta Health.

- Anderson, G.F., U.E. Reinhardt, P.S. Hussey, and V. Petrosyan. 2003. “It’s the Prices, Stupid: Why the United States Is so Different from Other Countries.” *Health Affairs* 22(3):89–105. <https://doi.org/10.1377/hlthaff.22.3.89>.
- Aubry, T., S. Farrell, S.W. Hwang, and M. Calhoun. 2013. “Identifying the Patterns of Emergency Shelter Stays of Single Individuals in Canadian Cities of Different Sizes.” *Housing Studies* 28(6):910–27. <https://doi.org/10.1080/02673037.2013.773585>.
- Aubry, T., P. Goering, S. Veldhuizen, C.E. Adair, J. Bourque, J. Distasio, E. Latimer, V. Stergiopoulos, J. Somers, D.L. Streiner, et al. 2016. “A Multiple-City RCT of Housing First with Assertive Community Treatment for Homeless Canadians with Serious Mental Illness.” *Psychiatric Services* 67(3):275–81. <https://doi.org/10.1176/appi.ps.201400587>.
- Calgary Homeless Foundation. 2014. *Point-in-Time Count Report*. At <http://calgaryhomeless.com/content/uploads/Winter-2014-PIT-Count-Report.pdf>.
- Cameron, A.C., and P.K. Trivedi. 2009. *Microeconometrics: Methods and Applications*. New York: Cambridge University Press.
- Clarkson, S., S. McIntyre, N. Noble, A. Li, S. Richardson, and J. Sinclair. 2017. *Family System Planning Framework*. Calgary: Calgary Homeless Foundation.
- Culhane, D., S. Metraux, and T. Hadley. 2002. “Public Service Reductions Associated with Placement of Homeless Persons with Severe Mental Illness in Supportive Housing.” *Housing Policy Debate* 13(1):107–64. <https://doi.org/10.1080/10511482.2002.9521437>.
- Drummond, M.F., M.J. Sculpher, G.W. Torrance, B.J. O’Brien, and G.L. Stoddart. 2005. *Methods for the Economic Evaluation of Health Care Programmes*, 3rd edition. Oxford, UK: Oxford University Press.
- Dutton, D.J., P.-G. Forest, R.D. Kneebone, and J.D. Zwicker. 2018. “Effect of Provincial Spending on Social Services and Health Care on Health Outcomes in Canada: An Observational Longitudinal Study.” *CMAJ* 190(3):E66–E71. <https://doi.org/10.1503/cmaj.170132>.
- Dutton, D.J., and A. Jadidzadeh. 2019. “The Incidence of Homelessness in Canada Is a Population-Level Phenomenon: A Comparison of Toronto and Calgary Shelter Use Over Time.” *Canadian Studies in Population* 46(2):161–71. <https://doi.org/10.1007/s42650-019-00013-8>.
- Falvo, N. 2009. *Homelessness, Program Responses, and an Assessment of Toronto’s Streets to Homes Program*. Ottawa: Canadian Policy Research Networks.
- Gaetz, S., E. Dej, T. Richter, and M. Redman. 2016. *The State of Homelessness in Canada 2016*. Toronto: Canadian Observatory on Homelessness.
- Gilmer, T.P., W.G. Manning, and S.L. Ettner. 2009. “A Cost Analysis of San Diego County’s REACH Program for Homeless Persons.” *Psychiatric Services* 60(4):445–50. <https://doi.org/10.1176/appi.ps.60.4.445>.
- Goering, P.N., D.L. Streiner, C. Adair, T. Aubry, J. Barker, J. Distasio, S.W. Hwang, J. Komaroff, E. Latimer, J. Somers, et al. 2011. “The At Home/Chez Soi Trial Protocol: A Pragmatic, Multi-Site, Randomised Controlled Trial of a Housing First Intervention for Homeless Individuals with Mental Illness in Five Canadian Cities.” *BMJ Open* 1(2):e000323. <https://doi.org/10.1136/bmjopen-2011-000323>.

- Goering, P.N., S. Veldhuizen, A. Watson, C. Adair, B. Kopp, E. Latimer, T. Aubry, G. Nelson, E. MacNaughton, D. Streiner, et al. 2014. *National Final Report Cross-Site At Home/Chez Soi Project*. Calgary: Mental Health Commission of Canada.
- Hwang, S.W. 2001. "Homelessness and Health." *CMAJ* 164(1):229–33.
- Hwang, S.W., C. Chambers, S. Chiu, M. Katic, A. Kiss, D.A. Redelmeier, and W. Levinson. 2013. "A Comprehensive Assessment of Health Care Utilization among Homeless Adults Under a System of Universal Health Insurance." *American Journal of Public Health* 103(Supplement 2):S294–301. <https://doi.org/10.2105/ajph.2013.301369>.
- Jadidzadeh, A., and N. Falvo. 2019. "Patterns of Exits from Housing in a Homelessness System of Care: The Case of Calgary, Alberta." *Housing Studies* 34(1):66–91. <https://doi.org/10.1080/02673037.2018.1432755>.
- Jadidzadeh, A., and R. Kneebone. 2018. "Patterns and Intensity of Use of Homeless Shelters in Toronto." *Canadian Public Policy/Analyse de politiques* 44(4):342–55. <https://doi.org/10.3138/cpp.2018-013>.
- Katz, A.S., S. Zerger, and S.W. Hwang. 2017. "Housing First the Conversation: Discourse, Policy and the Limits of the Possible." *Critical Public Health* 27(1):139–47. <https://doi.org/10.1080/09581596.2016.1167838>.
- Kneebone, R., M. Bell, N. Jackson, and A. Jadidzadeh. 2015. "Who Are the Homeless? Numbers, Trends and Characteristics of Those without Homes in Calgary." *SPP Research Papers* 8(11):16.
- Kuhn, R., and D.P. Culhane. 1998. "Applying Cluster Analysis to Test a Typology of Homelessness by Pattern of Shelter Utilization: Results from the Analysis of Administrative Data." *American Journal of Community Psychology* 26(2):207–32. <https://doi.org/10.1023/a:1022176402357>.
- Larimer, M.E., D.K. Malone, M.D. Garner, D.C. Atkins, B. Burlingham, H.S. Lonczak, K. Tanzer, J. Ginzler, S.L. Clifasefi, W.G. Hobson, et al. 2009. "Health Care and Public Service Use and Costs Before and After Provision of Housing for Chronically Homeless Persons with Severe Alcohol Problems." *JAMA* 301(13):1349–57. <https://doi.org/10.1001/jama.2009.414>.
- Li, A., N. Noble, S. Richardson, and J. Sinclair. 2017. *System Planning Framework*. Calgary: Calgary Homeless Foundation.
- Ly, A., and E. Latimer. 2015. "Housing First Impact on Costs and Associated Cost Offsets: A Review of the Literature." *Canadian Journal of Psychiatry* 60(11):475–87. <https://doi.org/10.1177/070674371506001103>.
- Rabinovitch, H., B. Pauly, and J. Zhao. 2016. "Assessing Emergency Shelter Patterns to Inform Community Solutions to Homelessness." *Housing Studies* 31(8):984–97. <https://doi.org/10.1080/02673037.2016.1165801>.
- Somers, J.M., A. Moniruzzaman, L. Currie, S.N. Rezansoff, A. Russolillo, and M. Parpouchi. 2016. "Accuracy of Reported Service Use in a Cohort of People Who Are Chronically Homeless and Seriously Mentally Ill." *BMC Psychiatry* 16(1):41. <https://doi.org/10.1186/s12888-016-0758-0>.
- Srebnik, D., T. Connor, and L. Sylla. 2013. "A Pilot Study of the Impact of Housing First—Supported Housing for Intensive Users of Medical Hospitalization and Sobering Services." *American Journal of Public Health* 103(2):316–21. <https://doi.org/10.2105/ajph.2012.300867>.
- Stergiopoulos, V., S.W. Hwang, A. Gozdzik, R. Nisenbaum, E. Latimer, D. Rabouin, C.E. Adair, J. Bourque, J. Connelly, J. Frankish, et al. 2015. "Effect of Scattered-Site Housing Using Rent Supplements and Intensive Case Management on Housing Stability among Homeless Adults with Mental Illness." *JAMA* 313(9):905–15. <https://doi.org/10.1001/jama.2015.1163>.
- Suttor, G. 2016. *Still Renovating: A History of Canadian Social Housing Policy*. Montreal: McGill-Queen's University Press.
- Taylor, L.A., A.X. Tan, C.E. Coyle, C. Ndumele, E. Rogan, M. Canavan, L.A. Curry, and E.H. Bradley. 2016. "Leveraging the Social Determinants of Health: What Works?" *PLoS One* 11(8):e0160217. <https://doi.org/10.1371/journal.pone.0160217>.
- Tsemberis, S. 2010. *Housing First: The Pathways Model to End Homelessness for People with Mental Health and Substance Use Disorders*. Center City, MN: Hazelden Publishing.
- Tsemberis, S., L. Gulcur, and M. Nakae. 2004. "Housing First, Consumer Choice, and Harm Reduction for Homeless Individuals with a Dual Diagnosis." *American Journal of Public Health* 94(4):651–6. <https://doi.org/10.2105/ajph.94.4.651>.
- Willse, C. 2010. "Neo-Liberal Biopolitics and the Invention of Chronic Homelessness." *Economy and Society* 39(2):155–84. <https://doi.org/10.1080/03085141003620139>.