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The effect of unemployment benefits on health: A propensity score analysis

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ABSTRACT

In the wake of the Great Recession, an expanding body of research has highlighted the role of social protection policies in mitigating the deleterious effects of adverse socioeconomic experiences. In this paper, we examine whether unemployment benefits – a key pillar of national social protection systems – can offset the negative health consequences of unemployment. Using cross-sectional nationally representative data from the Canadian Community Health Survey covering the period between 2009 and 2014, we employed propensity score matching to estimate the effect of receiving unemployment benefits on self-rated health among the unemployed. After matching benefit recipients to comparable non-recipient 'controls', we found that receiving unemployment benefits was associated with better health outcomes. In our main analyses, benefit recipiency reduced the probability of reporting poor self-rated health among the unemployed by up to 4.9% (95% CI −7.3, −2.5). Sensitivity analyses stratified by socioeconomic position revealed stronger treatment effects among lower income and less educated individuals. By contrast, treatment effects were small or negligible among higher income and more educated individuals. Our findings provide evidence that unemployment benefits can play an important role in offsetting the negative health consequences of unemployment among the socioeconomically disadvantaged. These findings lend support to recent calls, including many from within the field of public health, for governments to respond to current labor market trends by expanding the generosity and scope of social protection policies.

1. Introduction

The past several decades has borne witness to a marked decline in labour market conditions characterized by stagnant wages, the expansion of precarious work, and rising levels of structural unemployment (Keeley, 2015). In the field of public health, there is widespread concern that these deteriorating labor market conditions will produce adverse effects on the health of socioeconomically vulnerable populations (Benach et al., 2014; Catalano et al., 2011; Roelfs et al., 2011). Such concern has directed attention not only to the negative health consequences of recent labor market trends, but also to the role of social protection policies in mitigating their effects on the public's health (Benach et al., 2016; Loopstra et al., 2016; Ruckert and Labonté, 2017; Stuckler et al., 2009).

Against the backdrop of the Great Recession and subsequent jobs crisis, unemployment benefit programs have figured prominently in this rapidly expanding body of work on the health effects of social protection policies (Bambra and Eikemo, 2009; Cylus et al., 2014; Ferrarini et al., 2014; Norström and Grönqvist, 2015; O'Campo et al., 2015; Renahy et al., 2018; Shahidi et al., 2016; Voßemer et al., 2018). These programs are designed to provide temporary income support to workers who have lost their jobs. As a form of income maintenance, unemployment benefits can alleviate the financial strain associated with joblessness and ensure a modicum of access to health-promoting goods and services, such as food and shelter (Huijts et al., 2015; Macy et al., 2013). In addition to counteracting the material effects of job loss, unemployment benefits may provide psychological relief against the non-pecuniary consequences of joblessness, including the loss of

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identity and status otherwise afforded by gainful employment (Burgard and Lin, 2013; Paul and Moser, 2009). Accordingly, there is a strong theoretical case for the notion that unemployment benefits can function to protect the health of jobless individuals (O'Campo et al., 2015).

Despite these clear theoretical linkages, there are inherent difficulties in drawing causal inferences about the health effects of unemployment benefits. More specifically, such efforts are hindered by the presence of systematic differences in the underlying characteristics of recipients and non-recipients that render a direct comparison of these groups highly problematic (Cylus and Avendano, 2017). Most notably, because of strict eligibility criteria that require individuals to have worked a certain amount of time, recipients of unemployment benefits tend to exhibit a more favourable socioeconomic profile than their non-recipient counterparts. A key challenge that arises from these a priori differences is the need to separate out true benefit effects from the influence of selection bias and other sources of confounding (Grimes and Schulz, 2002). To address this challenge, scholars can exploit a range of quasi-experimental techniques, such as propensity score matching and synthetic control, which enable the construction of well-matched 'control' groups in situations where ideal comparison populations are not immediately obtainable from the available data (Basu et al., 2017).

Despite the widespread availability of these quasi-experimental techniques, a recent review of empirical literature on the health effects of unemployment benefit programs notes that extant studies in this area have relied overwhelmingly on descriptive methods that are not as equipped as their quasi-experimental counterparts to deal with the problem of selection bias (Renahy et al., 2018). While these studies tend to conclude that unemployment benefit recipiency is associated with better health outcomes (Ford et al., 2010; McLeod et al., 2012; Puig-Barrachina et al., 2011; Rodriguez, 2001; Rodriguez et al., 2001), their analyses do not take sufficient account of underlying differences between recipients and non-recipients and thus risk overestimating the strength of this association. In a more recent study, Cylus and Avendano (2017) make an effort to address this shortcoming of the existing literature by employing propensity score matching, in combination with more traditional linear probability modeling, to better account for potential selection effects. In a matched sample of unemployed Americans, they found that receiving unemployment benefits reduced the probability of reporting poor self-rated health by 3.0%. However, likely owing to a small and potentially underpowered sample, this effect did not reach the threshold of statistical significance. Thus, questions remain concerning the validity and strength of the observed association between unemployment benefits and health.

In the present study, we use propensity score matching to estimate the effect of unemployment benefit recipiency on self-rated health in a nationally representative sample of unemployed Canadians. Building on Cylus and Avendano's (2017) recent contribution to the literature on this topic, our study has the advantage of (i) drawing from a larger and therefore more powered sample of benefit recipients and (ii) making use of a more extensive set of matching algorithms to take fuller advantage of the strengths of propensity score methods.

2. Methods

2.1. Data and sample

We used data from the Canadian Community Health Survey (CCHS), the most comprehensive source of nationally representative data on the health of the Canadian population. We pooled annual cycles covering the period from 2009 to 2014. We excluded earlier cycles because they lacked an appropriate measure of unemployment benefit recipiency. We excluded later cycles due to a major survey redesign in 2015. Our sample consisted of adults 18–64 years of age who reported being unemployed and actively seeking work. We excluded residents of the northern territories (i.e. Yukon, Northwest Territories, and Nunavut) for whom equivalized household income data was unavailable. Because the missing rate for any given variable was relatively low (i.e. less than 2%), we applied listwise deletion to remove observations with missing data. The final sample consisted of 7558 individuals.

2.2. Exposure variable

The main exposure variable was unemployment benefit recipiency. In Canada, unemployment benefits are administered through the federal Employment Insurance (EI) program. To qualify for EI, claimants must also demonstrate that they lost their job through no fault of their own, are ready and willing to work, and are actively searching for paid employment opportunities. Individuals are also required to have worked a minimum number of insurable hours, which can range from 420 to 1400 h, depending on the individual's specific circumstances. In the CCHS, respondents are asked to identify sources of personal income. We defined individuals as unemployment benefit recipients if they reported EI as a source of personal income during the preceding year. Of the final sample of 7558 individuals, 2917 were defined as recipients and 4641 were defined as non-recipients. The benefit coverage rate of 38.6% observed in our sample is similar to those reported in other population-based surveys from the same time period, sitting approximately two percentage points below corresponding rates reported in the Canadian Labour Force Survey (Davis, 2012) and the Employment Insurance Coverage Survey (Statistics Canada, 2014a).

2.3. Outcome variables

The main outcome variable was self-rated health, a well-validated and widely used outcome (Jÿlha, 2009). Self-rated health was measured using a single five-item Likert scale that asked respondents to rate their general health status as "fair", "poor", "good", "very good", or "excellent". We collapsed the scale into a dichotomous outcome to distinguish between those who reported "fair" or "poor" health and those who reported "excellent", "very good", or "good" health. Dichotomous measures of self-rated health have been shown to be valid and reliable predictors of objective measures of health, including mortality (Idler and Benyamini, 1997; Lundberg and Manderbacka, 1996). In addition, prior analyses suggest that this approach produces similar results to alternative specifications which treat self-rated health as an ordered categorical outcome (Manor et al., 2000).

2.4. Empirical strategy

We used propensity score matching to estimate the effect of unemployment benefit recipiency on the probability of reporting self-rated health. As noted in our introduction, the presence of substantial differences in the underlying characteristics of benefit recipients and non-recipients may render them incomparable using standard regression methods, which assume that covariates follow a common distribution and functional form across groups (Quesnel-Vallée et al., 2010). If, as in the present case, relevant covariates are not distributed evenly across groups, this assumption can lead to appreciably biased estimates of exposure effects. In such a situation, propensity score methods provide an explicit framework for selecting comparable subsets of exposed and unexposed individuals from a given source population (Austin, 2011; Basu et al., 2017; Rosenbaum and Rubin, 1983). The goal is to approximate random assignment by constructing two groups that exhibit similar distributions on all known covariates and differ only with respect to treatment status; in this case, unemployment benefit recipiency.

We began by describing the key characteristics of the sample. Next, we estimated a propensity score for every individual, representing their probability of receiving unemployment benefits, conditional on a set of observed covariates that are known to predict both treatment assignment and health status. We included the following covariates: age (years), sex (male versus female), marital status (couple, single, or widowed/divorced), whether there are children living in the household, self-reported race/ethnicity (white, black, Aboriginal, Asian, or multiple/other), immigrant status (non-immigrant, immigrant less than 15 years, or immigrant 15 years or more), geographical region (Atlantic, Central, or Western), urbanicity (urban versus rural), education (less than secondary, secondary degree, some post-secondary, post-secondary degree), home ownership (owner versus renter), and survey year. We then matched recipients and non-recipients on the propensity score using five matching algorithms: nearest neighbour matching, caliper matching without replacement, caliper matching with replacement, kernel matching, and local linear matching. For a detailed description of these matching algorithms, see Caliendo and Kopeinig (2008). We assessed match quality by using two-sample t-tests to ensure that there were no significant differences in the distribution of covariates between matched recipients and non-recipient 'controls'. Assuming sufficient balance, we interpreted any remaining difference in the outcome as the average treatment effect on the treated (ATT).

A key assumption of propensity score matching is that treatment assignment is independent of the outcome conditional on the covariates used to estimate the propensity score (Austin, 2011). A key challenge in this respect is the dual role of income as both an independent predictor of benefit receipt and the principal mediating pathway by which unemployment benefits are hypothesized to affect health. While we control for some major socioeconomic factors (i.e. education and home ownership), the decision to exclude income from the initial pool of confounders may result in residual bias leading to an overestimation of benefit effects. On the other hand, because it is the key mediator between treatment and outcome, matching recipients and non-recipients on income levels may artificially attenuate benefit effects. Nevertheless, given the centrality of income to our hypothesis, we ran a second model where recipients and non-recipients were also matched on household income, in addition to the original set of covariates, to ascertain whether our results were sensitive to this analytic decision. However, to address the aforementioned challenge, we calculated a revised measure of household income in which the average annual EI benefit amount ($8246) was subtracted from the reported income values of individuals in the recipient group. This mitigated some of the concern around including income in the model, since after accounting for benefit receipt, income should be independent of treatment assignment. To calculate the annual average benefit amount, we multiplied the average duration of EI benefits by the average weekly benefit level over the study period – 21.7 weeks and $380, respectively (Statistics Canada, 2015). We included a second model in which recipients and non-recipients were matched on this revised household income measure.

A second major challenge concerns the lack of sufficient information on respondents' recent labor market history, which is likely to influence both benefit receipt and health status. For example, individuals who experience more frequent and longer spells of unemployment are both more likely to report adverse health-related events and also less likely to be eligible for benefits (Daly and Delaney, 2013; Employment Insurance Task Force, 2011; Garcy and Vågerö, 2012). To address this challenge, we treated chronic conditions as a proxy for labor market disadvantage – albeit a limited one – and ran a supplementary set of models in which we restricted our analysis to the subset of individuals who reported having no chronic conditions. While this approach does not eliminate the problem entirely (i.e. labor market disadvantage is not a perfect predictor of chronic conditions, and vice versa), the notion here is that, by removing a potential source of residual bias, we can derive a more conservative set of estimates for the effect of unemployment benefits on self-rated health. Chronic conditions were measured using a series of questions asking respondents to indicate whether they had ever been diagnosed with any of the following: asthma, chronic bronchitis, heart disease, cancer, diabetes, stroke, or Alzheimer's disease. We selected these conditions because they are listed among the leading causes of death in Canada and are known to shape labour market outcomes and employment stability among individuals (Eisner et al., 2002; Kamphuis et al., 2002; Koolhaas et al., 2014; Maaijwee et al., 2014; Sakata and Okumura, 2017; Short et al., 2005; Statistics Canada, 2014b; Tunceli et al., 2005). Due to sample size constraints, we were unable to run a similar analysis on the subset of individuals who reported having chronic conditions.

Following previous research (Lantis and Teahan, 2018), we conducted additional sensitivity analyses in which we stratified our main models by household income (bottom five deciles versus top five deciles), education (high school education or less versus more than a high school education), sex (men versus women), and age (44 years and below versus 45 years and above). By stratifying our models in this manner, we are able to examine heterogeneity in treatment effects across key sociodemographic groups, while simultaneously mitigating the influence of these variables as potential sources of confounding.

We also tested whether our results were sensitive to an alternative specification of the outcome variable, where "good" self-rated health was restricted to those who reported the "very good" or "excellent" categories.

We completed all analyses using Stata 13.0 (StataCorp LP, College Station, TX). We calculated standard errors based on 1000 repeated bootstrap samples.

3. Results

The key characteristics of the sample are presented in Tables 1 and 2. Before matching, we observed significant differences in the demographic and socioeconomic characteristics of benefit recipients and non-recipients. Recipients were older, more likely to be married and have no children, and more likely to live in a rural setting. Recipients reported higher household incomes and rates of home ownership. For example, only 10.2% of unemployment benefit recipients reported household incomes in the lowest decile, whereas 27.4% of non-recipients fell into this category. By contrast, recipients reported lower levels of educational attainment. For instance, the proportion of respondents with a post-secondary degree with 11.4% among recipients and 17.1% among non-recipients.

After matching recipients and non-recipients on the estimated propensity score, these differences were substantially reduced or even eliminated. As indicated by the post-match t-tests presented in Table 3, matched subsets of recipients and non-recipients exhibited no statistically significant differences in the relevant covariates at $p < 0.05$, indicating sufficient balance on these observed characteristics.

Treatment effects for our main analyses along with the number of observations selected in each match are listed in Table 4. In Model 1, which excluded household income from the propensity score estimation, benefit recipients reported consistently better health outcomes than their non-recipient 'controls'. Receiving benefits reduced the probability of reporting poor self-rated health by 3.6% (95% CI −6.3, −0.8) when using nearest neighbour matching, by 4.9% (95% CI −7.3, −2.5) when using caliper matching without replacement, by 4.0% (95% CI −6.7, −1.3) when using caliper matching with replacement, by 3.9% (95% CI −5.9, −1.9) when using kernel matching, and by 4.0% (95% CI −6.0, −2.0) when using local linear matching. In Model 2, we included an adjusted measure of household income in the estimation of the propensity score. Treatment effects in this second model were somewhat attenuated, though they retained their statistical significance. Receiving benefits reduced the probability of reporting poor self-rated health by 3.0% (95% CI −4.8, −1.2), 3.4% (95% CI −5.6, −1.2), 2.8% (95% CI −5.3, −0.3), 3.4% (95% CI −5.2, −1.6), and 3.2% (95% CI −5.6, −0.7), depending on the matching technique.

Treatment effects for our sensitivity analyses in which we restricted the sample to the subset of individuals who reported no chronic conditions are presented in Supplementary Table S1 of the online Appendix. These results did not differ substantially from those in our main analyses. In Model 1, estimates ranged from 3.3% (95% CI −6.0, −0.6) to 4.6% (95% CI −7.1, 2.1). In Model 2, they ranged from 2.6% (95%

Table 1
Demographic characteristics of the sample: CCHS (2009–2014).

	Employment Insurance Coverage	
	Yes	No
	N = 2798	N = 4331
Age		
18-24	6.9%	20.5%
25-34	19.3%	20.6%
35-44	21.9%	19.0%
45-54	25.5%	19.8%
55-64	26.5%	20.1%
Sex		
Male	58.3%	52.8%
Female	41.7%	47.2%
Marital Status		
Couple	51.5%	39.2%
Single	32.0%	46.0%
Widowed or divorced	16.5%	14.9%
Children		
None	65.0%	53.1%
One or more	35.0%	46.9%
Race		
White	84.5%	76.7%
Black	1.4%	2.6%
Aboriginal	7.5%	8.8%
Asian	4.8%	8.9%
Multiple or other	1.9%	3.0%
Immigrant Status		
Non-immigrant	89.7%	82.9%
Immigrant: < 15 years	4.1%	8.1%
Immigrant: 15 + years	6.2%	9.0%
Region		
Atlantic Canada	27.6%	11.6%
Central Canada	51.7%	56.6%
Western Canada	20.7%	31.8%
Area		
Urban	63.6%	78.7%
Rural	36.4%	21.3%
Year		
2009	19.6%	17.3%
2010	18.9%	17.2%
2011	16.5%	18.2%
2012	14.3%	16.3%
2013	16.1%	15.9%
2014	14.5%	15.0%

CI −4.6, −0.6) to 3.8% (95% CI −6.1, −1.4).

Treatment effects for our sensitivity analyses in which models were stratified by household income are listed in Tables 5 and 6. Among individuals who fell in the lower end of the income distribution, the treatment effects associated with receiving unemployment benefits were considerably larger than those estimated in our main analyses. Within this group, receiving benefits reduced the probability of reporting poor self-rated health by between 6.0% (95% CI −8.0, −4.0) and 6.8% (95% CI −10.5, −3.1), depending on the matching technique. In Model 2, where income was added to the pool of confounders, these treatment effects were substantially attenuated, though they remained sizeable and statistically significant. In this second model, receiving benefits reduced the probability of reporting poor self-rated health by up to 5.4% (95% CI −7.8, −3.0). By contrast, treatment effects among individuals who fell in the higher end of the income distribution were small and statistically insignificant in both Model 1 and Model 2.

Sensitivity analyses in which we stratified our models by education produced similar results to those reported in the preceding income-stratified models. These results are presented in Tables 7 and 8. Among individuals with a high school degree or less, receiving benefits reduced the probability of reporting poor self-rated health by between 5.1% (−9.4, −0.8) and 6.9% (95% CI −11.4, −2.4), depending on the matching technique. As in the preceding analyses, these estimates were

Table 2
Socioeconomic and health-related characteristics of the sample: CCHS (2009–2014).

	Employment Insurance Coverage	
	Yes	No
	N = 2798	N = 4331
Education		
Post-secondary degree	11.4%	17.1%
Some post-secondary	45.4%	38.8%
Secondary	24.5%	27.5%
Less than secondary	18.7%	16.6%
Home Ownership		
Renter	32.7%	43.4%
Owner	67.3%	56.6%
Household Income Decile		
1st	10.2%	27.4%
2nd	13.5%	13.1%
3rd	12.9%	9.6%
4th	11.5%	8.5%
5th	11.7%	8.0%
6th	10.8%	7.6%
7th	8.5%	7.8%
8th	8.6%	6.1%
9th	6.7%	5.7%
10th	5.6%	6.3%
Self-Rated Health		
Good	88.0%	85.2%
Poor	12.0%	14.8%
Chronic Conditions		
No	80.1%	79.2%
Yes	19.9%	20.8%

somewhat attenuated in Model 2, though they retained their statistical significance. Receiving benefits reduced the probability of reporting poor self-rated health by up to 5.4% (95% CI −7.4, −0.8) in this second model. Among individuals with more than a high school degree, treatment effects were relatively small and failed to reach the threshold of statistical significance in both Model 1 and Model 2.

Supplementary analyses in which we stratified our models by sex and age did not produce results that were substantially different from those reported in our main analyses. Similarly, estimated treatment effects were robust to an alternative specification of the outcome where "good" health included only the "very good" and "excellent" response categories. Results from these additional analyses are reported in Supplementary Tables S2 through S6 of the online Appendix, respectively.

4. Discussion

Prior literature suggests that unemployment benefits may play a role in protecting the health of jobless individuals (O'Campo et al., 2015). Several studies have documented how unemployment benefit recipients report better physical and mental health outcomes than their non-recipient counterparts (Cylus and Avendano, 2017; Ford et al., 2010; McLeod et al., 2012; Puig-Barrachina et al., 2011; Rodriguez, 2001; Rodriguez et al., 2001). With the aim of contributing to this available body of evidence, the present study employed propensity score methods to better account for underlying differences in the characteristics of benefit recipients and non-recipients that may bias the estimation of the health effects of unemployment benefit programs.

In our sample, unemployment benefit recipients differed substantially from their non-recipient counterparts with respect to key factors such as income, education, home ownership, and marital status. On balance, recipients exhibited a more favourable demographic and socioeconomic profile, highlighting the role of these variables as potential sources of confounding that might influence the association between unemployment benefit recipiency and self-rated health. Our

Table 3
Assessment of covariate balance before and after matching: CCHS (2009–2014).

	Unmatched		Nearest Neighbour		Caliper Without Replacement		Caliper With Replacement		Kernel		Local Linear	
	t-test	p-value	*t*-test	p-value	*t*-test	p-value	*t*-test	p-value	*t*-test	p-value	*t*-test	p-value
Age												
18-24	−16.68	0.000	−0.45	0.651	−0.05	0.956	−0.42	0.675	−0.13	0.893	−0.40	0.700
25-34	−1.57	0.116	0.77	0.442	−1.07	0.285	−0.67	0.504	0.54	0.588	0.00	1.000
35-44	3.15	0.002	0.48	0.632	0.66	0.512	−0.65	0.516	−0.45	0.653	−1.78	0.075
45-54	6.27	0.000	−1.37	0.17	0.04	0.970	0.69	0.489	−0.54	0.587	0.00	1.000
55-64	6.72	0.000	0.51	0.612	0.37	0.711	0.82	0.412	0.56	0.576	1.83	0.060
Female	−4.46	0.000	−0.71	0.475	0.83	0.405	0.00	1.000	−0.65	0.516	−1.11	0.267
Marital Status												
Married or cohabitating	10.87	0.000	−0.31	0.753	−1.54	0.125	0.62	0.532	0.39	0.697	−0.03	0.979
Widowed or divorced	2.00	0.046	0.43	0.669	0.84	0.400	−0.04	0.970	−0.36	0.720	0.14	0.887
Single	−12.45	0.000	−0.05	0.956	0.92	0.356	−0.63	0.531	−0.13	0.896	−0.08	0.933
Children												
Yes	−10.81	0.000	0.25	0.799	−0.30	0.768	0.12	0.906	0.14	0.887	1.19	0.236
Race												
White	8.62	0.000	−1.07	0.284	−1.35	0.178	−1.61	0.108	0.19	0.847	−1.07	0.284
Black	−3.56	0.000	0.45	0.653	0.50	0.614	0.90	0.368	−0.51	0.613	0.45	0.653
Aboriginal	−2.46	0.014	0.77	0.444	0.39	0.699	0.66	0.509	0.36	0.716	0.77	0.444
Asian	−6.75	0.000	−0.12	0.902	0.76	0.448	0.33	0.745	−0.41	0.680	−0.12	0.902
Mixed or other	−3.22	0.001	1.25	0.212	1.10	0.270	0.76	0.447	−0.11	0.913	1.25	0.212
Immigrant Status												
Non-immigrant	8.13	0.000	0.68	0.497	−1.50	0.134	−1.41	0.159	0.86	0.389	0.43	0.670
Immigrant < 15 years	−6.86	0.000	−0.77	0.441	0.75	0.455	0.27	0.784	−0.54	0.587	−0.26	0.795
Immigrant 15 + years	−4.27	0.000	−0.22	0.829	1.26	0.207	1.87	0.062	−0.64	0.524	−0.32	0.747
Region												
Atlantic	17.41	0.000	−0.56	0.579	1.03	0.301	0.14	0.886	0.17	0.864	0.41	0.681
Central	−3.64	0.000	−0.18	0.854	−0.06	0.948	−0.32	0.752	0.31	0.757	−0.47	0.637
Western	−10.76	0.000	0.85	0.396	−0.81	0.420	0.24	0.812	−0.57	0.571	0.13	0.897
Urban	14.81	0.000	0.16	0.870	−0.04	0.971	1.06	0.290	1.1	0.273	1.59	0.112
Education												
Post-secondary degree	−6.35	0.000	−0.61	0.539	−0.66	0.509	0.39	0.694	−0.56	0.573	0.08	0.934
Some post-secondary	6.15	0.000	−0.87	0.385	−0.26	0.798	−1.17	0.243	0.06	0.950	−0.32	0.752
Secondary	−3.39	0.001	0.21	0.831	−0.40	0.687	0.00	1.000	−0.05	0.957	−0.81	0.415
Less than secondary	1.88	0.060	1.4	0.163	1.40	0.161	1.21	0.226	0.44	0.659	1.26	0.209
Home Owner	9.25	0.000	0.86	0.389	0.72	0.474	1.03	0.301	1.09	0.277	0.08	0.933
Year												
2009	2.63	0.009	−0.10	0.921	0.16	0.871	−1.00	0.316	0.02	0.981	−1.44	0.151
2010	2.08	0.038	−1.85	0.065	−0.12	0.901	0.36	0.716	−0.66	0.507	−0.03	0.973
2011	−2.06	0.040	0.21	0.831	0.97	0.332	1.31	0.189	−0.24	0.808	0.75	0.452
2012	−2.05	0.041	1.87	0.061	−0.62	0.532	−0.88	0.379	0.22	0.827	0.04	0.970
2013	−0.02	0.982	1.33	0.185	0.39	0.697	0.31	0.758	0.45	0.653	0.11	0.915
2014	−0.77	0.442	−1.21	0.227	−0.85	0.393	−0.08	0.936	0.28	0.778	0.75	0.453

Table 4
Average treatment effect (ATT) of employment insurance on unemployed Canadians: CCHS (2009–2014).

	Model 1			Model 2		
	ATT	SE	p-value	ATT	SE	p-value
Poor Self-Rated Health						
Nearest Neighbour	**−0.036**	**0.014**	**0.013**	**−0.030**	**0.009**	**0.001**
Caliper, without replacement	**−0.049**	**0.012**	**0.000**	**−0.034**	**0.011**	**0.002**
Caliper, with replacement	**−0.040**	**0.014**	**0.005**	**−0.028**	**0.013**	**0.040**
Kernel	**−0.039**	**0.010**	**0.000**	**−0.034**	**0.009**	**0.000**
Local Linear	**−0.040**	**0.010**	**0.001**	**−0.032**	**0.013**	**0.023**
Observations						
Unmatched	T = 2917	C = 4641		T = 2917	C = 4641	
Nearest Neighbour	T = 2911	C = 2911		T = 2895	C = 2895	
Caliper, without replacement	T = 1970	C = 1970		T = 1962	C = 1962	
Caliper, with replacement	T = 2481	C = 1388		T = 2449	C = 1509	
Kernel	T = 2911	C = 4605		T = 2895	C = 4620	
Local Linear	T = 2911	C = 1448		T = 2895	C = 1581	

Notes:Model 1 includes age, sex, marital status, children, race, immigrant status, geographical region, urbanicity, education, home ownership, and survey year.
Model 2 includes all covariates in Model 1 plus equivalized household income, measured in deciles and adjusted for benefit receipt.
Caliper width is set to 0.2 of the standard deviation of the logic of the propensity score (Austin, 2011).
Abbreviations: ATT, Average Treatment Effect on the Treated; SE, standard error; T, treatment; C, control.

Table 5
Average treatment effect (ATT) of employment insurance on unemployed Canadians in the bottom five deciles of household income: CCHS (2009–2014).

	Model 1			Model 2		
	ATT	SE	p-value	ATT	SE	p-value
Poor Self-Rated Health						
Nearest Neighbour	**−0.066**	**0.018**	**0.000**	**−0.046**	**0.018**	**0.009**
Caliper, without replacement	**−0.063**	**0.016**	**0.000**	**−0.040**	**0.016**	**0.012**
Caliper, with replacement	**−0.068**	**0.019**	**0.001**	**−0.051**	**0.017**	**0.003**
Kernel	**−0.060**	**0.010**	**0.000**	**−0.054**	**0.012**	**0.000**
Local Linear	**−0.066**	**0.013**	**0.000**	**−0.051**	**0.017**	**0.003**
Observations						
Unmatched	T = 1756	C = 3112		T = 1756	C = 3112	
Nearest Neighbour	T = 1754	C = 1754		T = 1731	C = 1731	
Caliper, without replacement	T = 1188	C = 1188		T = 1096	C = 1096	
Caliper, with replacement	T = 1463	C = 924		T = 1344	C = 951	
Kernel	T = 1754	C = 3106		T = 1731	C = 3092	
Local Linear	T = 1754	C = 996		T = 1731	C = 1041	

Notes:Model 1 includes age, sex, marital status, children, race, immigrant status, geographical region, urbanicity, education, home ownership, and survey year.
Model 2 includes all covariates in Model 1 plus equivalized household income, measured in deciles and adjusted for benefit receipt.
Caliper width is set to 0.2 of the standard deviation of the logic of the propensity score (Austin, 2011).
Abbreviations: ATT, Average Treatment Effect on the Treated; SE, standard error; T, treatment; C, control.

results suggest that the positive association between unemployment benefits and health persists even after using a method that more appropriately controls for the influence of these confounding factors. Despite concerns that prior studies may have overestimated the health effects of unemployment benefit programs by neglecting the full extent of differences between recipients and non-recipients (Cylus and Avendano, 2017), our findings are consistent with the existing literature on this topic (Renahy et al., 2018). Put simply, they support the notion that, by maintaining the income of those who experience job loss, unemployment benefits can simultaneously serve to maintain their health. Specifically, after using the estimated propensity score to match unemployed benefit recipients to comparable non-recipient ‘controls’, we found that benefit receipt was associated with sizeable and robust reductions in the probability of reporting poor self-rated health.

Notably, results from our sensitivity analyses suggest that the positive association between unemployment benefit recipiency and self-rated health is only observed among lower income and less educated individuals. In fact, we found no statistically significant treatment effects among their higher income and more educated counterparts. Thus, just as the direct effect of unemployment has been shown to vary by socioeconomic position (Norström et al., 2014), these results suggest that the health effects of unemployment benefits, while strongly protective among more socioeconomically disadvantaged individuals, may be small or, as in the case of our study, even negligible among less socioeconomically disadvantaged individuals. Within the broader population health literature, there is growing recognition that the reporting of average treatment effects can be highly problematic, given the possibility of heterogeneous responses to a similar exposure (Subramanian et al., 2018). In line with these concerns, our findings suggest that, by taking an undifferentiated view of the question, prior studies on the health effects of unemployment benefits have potentially underestimated its protective role among the socioeconomically disadvantaged and overestimated its impact among their more socioeconomically advantaged counterparts. Future research could examine whether the heterogeneous treatment effects observed in the present study are also found in other jurisdictions.

The above findings notwithstanding, caution is warranted in the interpretation of our results and a causal interpretation of the study results should be avoided. While we used a method well-suited to account for potential selection effects, our study results may be biased by unmeasured sources of confounding. For example, due to data limitations, we were unable to match recipients and non-recipients on an extensive set of socioeconomic characteristics (e.g. wealth, occupational sector, and duration of unemployment), despite the central role

Table 6
Average treatment effect (ATT) of employment insurance on unemployed Canadians in the top five deciles of household income: CCHS (2009–2014).

	Model 1			Model 2		
	ATT	SE	p-value	ATT	SE	p-value
Poor Self-Rated Health						
Nearest Neighbour	0.003	0.018	0.885	0.006	0.012	0.582
Caliper, without replacement	−0.013	0.014	0.349	0.005	0.013	0.708
Caliper, with replacement	−0.004	0.017	0.822	0.014	0.016	0.376
Kernel	0.004	0.016	0.813	0.005	0.013	0.700
Local Linear	0.003	0.014	0.818	0.006	0.017	0.726
Observations						
Unmatched	T = 1161	C = 1475		T = 1161	C = 1475	
Nearest Neighbour	T = 1152	C = 1152		T = 1136	C = 1136	
Caliper, without replacement	T = 829	C = 829		T = 810	C = 810	
Caliper, with replacement	T = 1067	C = 541		T = 1084	C = 573	
Kernel	T = 1152	C = 1475		T = 1136	C = 1520	
Local Linear	T = 1152	C = 543		T = 1136	C = 573	

Notes:Model 1 includes age, sex, marital status, children, race, immigrant status, geographical region, urbanicity, education, home ownership, and survey year.
Model 2 includes all covariates in Model 1 plus equivalized household income, measured in deciles and adjusted for benefit receipt.
Caliper width is set to 0.2 of the standard deviation of the logic of the propensity score (Austin, 2011).
Abbreviations: ATT, Average Treatment Effect on the Treated; SE, standard error; T, treatment; C, control.

Table 7
Average treatment effect (ATT) of employment insurance on unemployed Canadians with a high school education or less: CCHS (2009–2014).

	Model 1			Model 2		
	ATT	SE	p-value	ATT	SE	p-value
Poor Self-Rated Health						
Nearest Neighbour	**−0.051**	**0.015**	**0.000**	**−0.030**	**0.013**	**0.016**
Caliper, without replacement	**−0.060**	**0.020**	**0.003**	**−0.034**	**0.013**	**0.009**
Caliper, with replacement	**−0.069**	**0.023**	**0.002**	**−0.041**	**0.017**	**0.016**
Kernel	**−0.052**	**0.015**	**0.000**	**−0.039**	**0.016**	**0.015**
Local Linear	**−0.051**	**0.022**	**0.021**	−0.039	0.022	0.076
Observations						
Unmatched	T = 1271	C = 2109		T = 1271	C = 2109	
Nearest Neighbour	T = 1270	C = 1270		T = 1261	C = 1261	
Caliper, without replacement	T = 695	C = 695		T = 654	C = 654	
Caliper, with replacement	T = 904	C = 569		T = 961	C = 586	
Kernel	T = 1270	C = 2094		T = 1261	C = 2090	
Local Linear	T = 1270	C = 658		T = 1261	C = 686	

Notes:Model 1 includes age, sex, marital status, children, race, immigrant status, geographical region, urbanicity, education, home ownership, and survey year.
Model 2 includes all covariates in Model 1 plus equivalized household income, measured in deciles and adjusted for benefit receipt.
Caliper width is set to 0.2 of the standard deviation of the logic of the propensity score (Austin, 2011).
Abbreviations: ATT, Average Treatment Effect on the Treated; SE, standard error; T, treatment; C, control.

these factors play in determining both health and benefit status. Unfortunately, information on these characteristics is not routinely collected in health surveys such as the CCHS. While such information is more readily available in longitudinal surveys on labor and income, these latter surveys suffer from very small sample sizes. As an alternative approach, future work in this area may seek to link health surveys to administrative records that cover a more comprehensive set of socioeconomic characteristics (Mah et al., 2017).

Our study is limited in several other important respects. First, because we tested our hypothesis at the individual-level, we are unable to comment on whether the positive association between unemployment benefits and health observed in our study translates at the aggregate level. Nevertheless, studies in the existing literature do support the notion that societies with more generous unemployment benefit systems exhibit better health outcomes and narrower work-related health inequalities (Ferrarini et al., 2014; McLeod et al., 2012; Shahidi et al., 2016; Voβemer et al., 2018).

Second, by virtue of the cross-sectional nature of our data, the temporal ordering between our exposure and outcomes of interest could not be established. Given that poor health can be a contributing factor to labour market exit and subsequent take-up of unemployment benefits (Virtanen et al., 2013), the presented results may be biased by our inability to control for prior health status. Similarly, in the absence of longitudinal data, we were unable to control for prior income, a factor which as noted earlier can result in the overestimation of the health effects of unemployment benefits.

Third, our outcome measures rely on self-reported data and thus suffer from any corresponding biases. For example, if we are correct in assuming that recipients and non-recipients are socioeconomically distinct groups, they may subjectively interpret their health in different ways (Quesnel-Vallée, 2007). Future research should aim to replicate these findings using a broader set of indicators, including more objective measures of health status, including those available in administrative health records.

Finally, it is possible that some of the confounders we included in our estimation of the propensity score are correlated to the level of benefits received. Due to data limitations, we are unable to test this problem directly. Nevertheless, matching on these factors may result in attenuated benefit effects, giving further need for caution in the interpretation of our study results.

5. Conclusion

Our study highlights the role that unemployment benefits can

Table 8
Average treatment effect (ATT) of employment insurance on unemployed Canadians with more than a high school degree: CCHS (2009–2014).

	Model 1			Model 2		
	ATT	SE	p-value	ATT	SE	p-value
Poor Self-Rated Health						
Nearest Neighbour	−0.021	0.011	0.056	−0.021	0.011	0.055
Caliper, without replacement	**−0.032**	**0.014**	**0.022**	−0.007	0.015	0.642
Caliper, with replacement	−0.024	0.018	0.183	−0.005	0.016	0.750
Kernel	**−0.026**	**0.011**	**0.018**	−0.016	0.012	0.188
Local Linear	−0.027	0.018	0.133	−0.016	0.016	0.324
Observations						
Unmatched	T = 1646	C = 2533		T = 1646	C = 2533	
Nearest Neighbour	T = 1641	C = 1641		T = 1636	C = 1636	
Caliper, without replacement	T = 1097	C = 1097		T = 899	C = 899	
Caliper, with replacement	T = 1388	C = 672		T = 1130	C = 796	
Kernel	T = 1641	C = 2522		T = 1636	C = 2524	
Local Linear	T = 1641	C = 730		T = 1636	C = 918	

Notes:Model 1 includes age, sex, marital status, children, race, immigrant status, geographical region, urbanicity, education, home ownership, and survey year.
Model 2 includes all covariates in Model 1 plus equivalized household income, measured in deciles and adjusted for benefit receipt.
Caliper width is set to 0.2 of the standard deviation of the logic of the propensity score (Austin, 2011).
Abbreviations: ATT, Average Treatment Effect on the Treated; SE, standard error; T, treatment; C, control.

potentially play in offsetting the negative health impact of unemployment. Using propensity score matching to construct the most suitable comparisons possible, we showed that unemployed individuals in receipt of benefits report consistently better self-rated health than non-recipient 'controls'. Departing from the existing literature on this topic, however, our results also suggest that this positive association is restricted to those who fall in the lower end of the income distribution. Although these results were consistent across several different matching algorithms, caution is warranted and a causal interpretation should be avoided, given the cross-sectional nature of the data and our inability to control for several important unmeasured sources of confounding. In addition to making an empirical contribution to the literature, our study offers some important insights for the future of social and economic policymaking. Labor market insecurity is on the rise in many advanced capitalist countries (Keeley, 2015). Partly as a result of these adverse labor market trends, the prevalence of low-wage jobs is growing and fewer workers than ever qualify to receive unemployment benefits and other forms of social protection (Davis, 2012; Kalleberg, 2018). The confluence of these factors may, in turn, explain the growing number of studies documenting widening socioeconomic health inequalities, including those between employed and unemployed persons (Barr et al., 2017; Bor et al., 2017; Farrants et al., 2016; Hajizadeh et al., 2016; Kroll and Lampert, 2011; Nelson and Tøge, 2017; van der Wel et al., 2018). Our study lends support to recent calls, including many from within the field of public health, for governments to respond to these troubling developments by expanding the generosity and scope of existing social protection policies (Loopstra et al., 2016; Ruckert and Labonté, 2017; Schrecker and Milne, 2015; Stuckler et al., 2010).

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.socscimed.2019.02.047.

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