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Using Marginal Structural Modeling to Estimate the Cumulative Impact of an Unconditional Tax Credit on Self-Rated Health

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In previous studies, researchers estimated short-term relationships between financial credits and health outcomes using conventional regression analyses, but they did not account for time-varying confounders affected by prior treatment (CAPTs) or the credits' cumulative impacts over time. In this study, we examined the association between total number of years of receiving New Zealand's Family Tax Credit (FTC) and self-rated health (SRH) in 6,900 working-age parents using 7 waves of New Zealand longitudinal data (2002–2009). We conducted conventional linear regression analyses, both unadjusted and adjusted for time-invariant and time-varying confounders measured at baseline, and fitted marginal structural models (MSMs) that more fully adjusted for confounders, including CAPTs. Of all participants, 5.1%–6.8% received the FTC for 1–3 years and 1.8%–3.6% for 4–7 years. In unadjusted and adjusted conventional regression analyses, each additional year of receiving the FTC was associated with 0.033 (95% confidence interval (CI): −0.047, −0.019) and 0.026 (95% CI: −0.041, −0.010) units worse SRH (on a 5-unit scale). In the MSMs, the average causal treatment effect also reflected a small decrease in SRH (unstabilized weights: $\beta = -0.039$ unit, 95% CI: −0.058, −0.020; stabilized weights: $\beta = -0.031$ unit, 95% CI: −0.050, −0.007). Cumulatively receiving the FTC marginally reduced SRH. Conventional regression analyses and MSMs produced similar estimates, suggesting little bias from CAPTs.

cohort studies; confounding factors; health status; income; New Zealand; parents; public policy

Abbreviations: ACTE, average causal treatment effect; CAPTs, confounders affected by prior treatment; CI, confidence interval; FTC, Family Tax Credit; IPTWs, inverse probability of treatment weights; MSMs, marginal structural models; SD, standard deviation; SoFIE, Survey of Family, Income and Employment; SRH, self-rated health.

An important question in both social policy and social epidemiology is whether the provision of financial credits improves health. Financial credits are hypothesized to influence health by impacting material circumstances, psychosocial factors, and/or employment through increasing income (1). Theoretically, they could beneficially affect, adversely affect, or not affect health outcomes (1). For example, recipients could spend the additional income from financial credits on goods and services that may improve health (e.g., nutrient-rich food), worsen health (e.g., tobacco), or neither improve nor worsen health.

Previous empirical studies have found little evidence for short-term associations between financial credits and health outcomes in high-income countries (2, 3), including New Zealand (4, 5). These studies generally used individual fixed-effects regression models (6), which are—by design—focused on detecting the short-term health changes resulting from income changes and are limited in their ability to estimate any health changes that might accumulate over time. (They also cannot estimate average causal treatment effects (ACTEs), because they only identify people who experienced temporal change in treatment or outcome.) Financial credits may affect health not through the short-term boost in living standards that they provide but through supplementing income sustainably over a longer period of years, thereby enabling recipients to build the economic basis for improving their health (4, 5, 7). Therefore, researchers have called for studies investigating the long-term health impacts of financial credits (4, 5, 7, 8). However, to our knowledge, cumulative associations between financial credits and health outcomes have not been studied.

Because previous studies used conventional regression models, they may have suffered from bias due to insufficient control for time-varying confounders affected by prior treatment (CAPTs) (3–5). Time-varying confounding is tricky to address using conventional approaches. Neglecting to control for CAPTs runs the risk of confounding, but statistically controlling for these variables can also introduce bias because they also mediate the relationship between exposure and future outcome status (3–5). Previous studies have also failed to adjust for health selection (or reverse causation, where the outcome variable in an earlier time period influences the exposure value at a subsequent wave) and treatment history (a person's specific "regimen" of treatment over time).

Marginal structural models (MSMs) were specifically developed for dealing with time-varying confounding (as well as health selection and treatment history) and for estimating cumulative associations (9, 10). MSMs provide an unbiased estimate of the ACTE under the 5 assumptions of 1) exchangeability (i.e., no unmeasured confounding); 2) positivity (i.e., the existence of participants with different exposure levels within strata of confounding (11)); 3) consistency (i.e., treatment variation is irrelevant (12)); 4) correct model(s) specification; and 5) no measurement error (9, 10). Despite MSM methods' being well suited for studying the health changes resulting from financial credits and other social interventions, to our knowledge no previous study has applied these methods for this purpose.

The Family Tax Credit (FTC) is an unconditional (given without obligation) tax credit that aims to increase income among families living in poverty or at risk of poverty in New Zealand (13). As per the Taxation (Working For Families) Act 2004 (14), to be FTC-*eligible*, persons are required to: be New Zealand residents; be ≥16 years old; be principal caretakers of a dependent child; and have family incomes within bounds defined by the number of dependent children in the family (e.g., see reference 15 for 2007). After filing for the FTC, eligible families generally receive the credit as a regular lump-sum payment through the tax system (16). The maximum amount of FTC for a family with 2 dependent children in 2007 was $7,252 (approximately 20% of per-capita gross national income) (15). Between October 2004 and April 2007, the New Zealand government expanded the generosity and population coverage of the FTC through its Working For Families welfare reform measure (16), providing a natural experiment on income supplementation (5). Previously, we conducted a fixed-effects regression analysis and found no discernible change in self-rated health (SRH; measured on a 5-unit scale) associated with becoming eligible for the FTC ($\beta = 0.01$ unit, 95% confidence interval (CI): −0.01, 0.04) or receiving income increases through the FTC ($\beta = 0.00$ unit, 95% CI: −0.01, 0.00) *over the short term* (4). (Other social interventions (e.g., flexible working conditions) influence SRH relatively immediately (17).) However, whether receipt of the FTC over many years has a cumulative association with health has not previously been studied.

Figure 1 shows hypothesized relationships between total number of years of receiving the FTC over 3 waves of a longitudinal study (wave$_t$ to wave$_{t+2}$) and SRH at wave 7. (The diagram could be expanded to cover more waves of data.) The causal diagram suggests that each of the determinants of FTC could be a time-varying confounder (confounding through

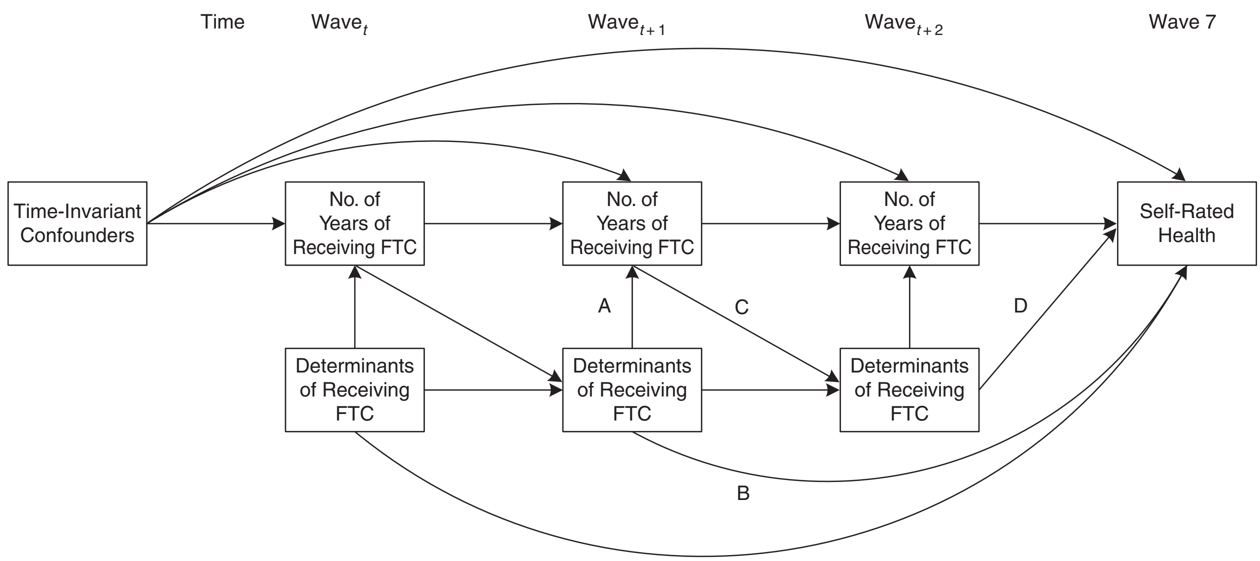

Figure 1. Hypothesized relationship between the total number of years of receiving New Zealand's Family Tax Credit (FTC) over 3 waves (wave$_t$ to wave$_{t+2}$) of the Survey of Family, Income and Employment (2002–2009) and self-rated health at wave 7, detailing causal pathways operating through time-invariant confounders and time-varying determinants of receiving the FTC. Time-invariant confounders included age, sex, ethnicity, and education. Time-varying determinants of receiving the FTC were family income (minus FTC), number of dependent children, and family type. The letters A–D depict hypothesized relationships between 2 variables (e.g., A denotes the causal influence of the determinants of FTC receipt at wave$_t$ on the total number of years of FTP receipt at wave$_t$). The diagram suggests that each of the determinants of receiving FTC could be a time-varying confounder (confounding through pathway A-B) that could be affected by prior treatment (mediation through pathway C-D).

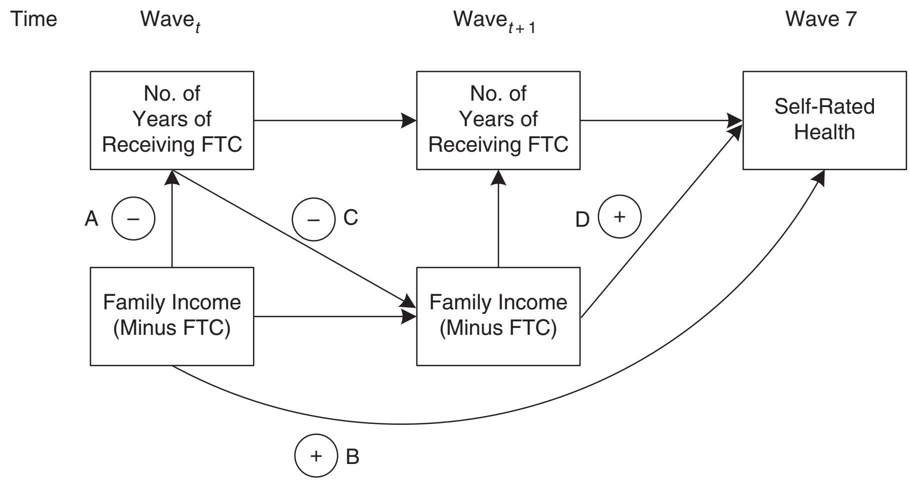

Figure 2. Hypothesized relationship between the total number of years of receiving New Zealand's Family Tax Credit (FTC) over 3 waves (wave$_t$ to wave$_{t+2}$) of the Survey of Family, Income and Employment (2002–2009) and self-rated health at wave 7, detailing the directions of the causal associations of a determinant of receiving the FTC (family income (minus FTC)) that could contemporaneously confound and mediate the exposure-outcome relationship. The letters A–D depict hypothesized relationships between 2 variables (e.g., A denotes the causal influence of family income (minus FTC) at wave$_t$ on the total number of years of FTP receipt at wave$_t$). The diagram suggests that the combination of the directions of the time-varying confounding and mediation pathways of the determinant of FTP receipt could produce a spuriously null finding for the exposure-outcome relationship in conventional regression analyses (see VanderWeele et al. (19) for rules).

pathway A-B in Figure 1) that could be affected by prior treatment (mediation through pathway C-D). For example, it is hypothesized that family income is a confounding variable, since it determines FTC receipt (pathway A-B in Figure 2), as well as potentially being a mediating variable, since (in theory (18)) receiving the FTC might lower subsequent non-FTC sources of family income by reducing the number of hours worked (pathway C-D).

Regarding the direction of confounding, assuming monotonicity, family income at wave$_t$ has a negative association with number of years of FTC receipt at wave$_t$ (pathway A) and a positive association with SRH at wave 7 (pathway B), suggesting that confounding results in underestimation of treatment effects (see VanderWeele et al. (19) for rules; Figure 2). In terms of mediation, number of years of receiving the FTC at wave$_t$ is hypothesized to have a negative dose-response association with family income at wave$_{t+1}$ (pathway C in Figure 2), while family income at wave$_{t+1}$ is hypothesized to have a positive monotonic association with SRH at wave 7 (pathway D). Given that confounding and mediation biases operate in different directions, if the strengths of these biases are similar they may cancel each other out and produce a spuriously null finding in a conventional regression analysis (regardless of whether or not the results are adjusted for these variables). Therefore, family income could theoretically be a CAPT, and this could result in bias in conventional regression analyses. Equivalently, the other 2 determinants of FTC receipt (i.e., number of dependent children and family type) could be CAPTs. Previous studies have raised concerns about bias from CAPTs in studies examining tax credit–health relationships (4, 5).

In this study, we estimated the cumulative causal association of FTC receipt with SRH among adults in New Zealand using marginal structural modeling to ensure stronger adjustment for measured CAPTs. Methodologically, the study compared findings from conventional regression analytical models and MSMs to determine the presence and magnitude of bias from CAPTs. More specifically, it answered 2 research questions: 1) What is the ACTE between each additional year of receiving the FTC (over a 7-year study period) and SRH at wave 7 among adults in New Zealand? 2) Do estimates from conventional regression analyses (no control for CAPTs) differ from those from MSMs (stronger control for CAPTs), indicating risk of bias from CAPTs?

METHODS

Study design

The University of Otago (Wellington, New Zealand) Human Ethics Committee granted ethics approval for this study. Seven waves of data (2002–2009) were extracted from the Survey of Family, Income and Employment (SoFIE) (http://www.stats.govt.nz/survey-participants/a-z-of-our-surveys/survey-of-family-income-and-employment.aspx, data version V.2), a representative longitudinal study conducted by Statistics New Zealand between October 2002 and September 2010 (20). The SoFIE investigators collected data from a representative sample of the New Zealand population residing in non-institutionalized households, interviewing 29,790 persons (>22,000 adults) in 11,500 households at wave 1 baseline (20). These original sample members were followed up annually over the 7-year study period (see Carter et al. (20) for full cohort profile). We restricted the survey sample to 6,900 working-age (19–65 years) parents in 1- or 2-parent families who responded during all 7 waves of the study (Figure 3).

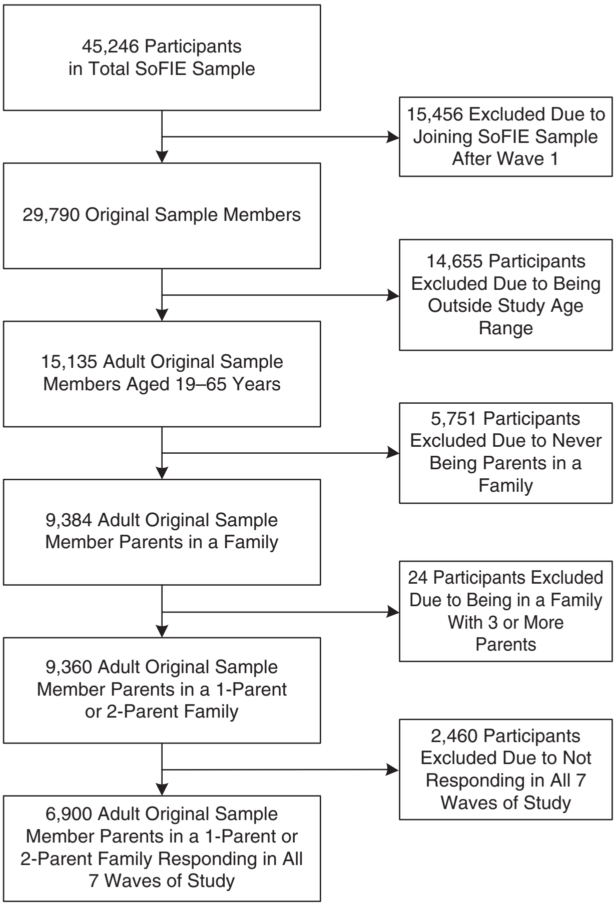

Figure 3. Selection of the current study sample from participants in the Survey of Family, Income and Employment (SoFIE), 2002–2009.

Exposure

Our exposure was the total number of years a participant received the FTC over the 7-year study period, a continuous variable ranging from 0 to 7. We preferred this exposure over the total dollar amount of FTC received, because receipt itself may be as important for improving social outcomes as the specific amount received (1, 21, 22). Previous MSM studies have also used cumulative measures (i.e., numbers of time units over which participants received the treatment of interest) as the exposures (23, 24). We determined, for each wave, whether a participant self-reported receiving the FTC. Information on receipt of the FTC over the previous year was collected from the participants at each wave in the SoFIE income module, using the following question (pertaining to the past year only): "Looking at this calendar, can you tell me when you received the Family Tax Credit?". From these data, we calculated for each participant the total number of years of receiving the FTC over the 7-year study period.

Our previous fixed-effects regression analysis defined the exposure differently; namely, we estimated *eligibility* for the FTC and the amount of FTC that a family was *eligible for*, because we sought to estimate the intention-to-treat effect rather than an ACTE (4). Eligibility for the FTC and receipt of the FTC are not perfectly correlated, because of imperfect administration of the tax credit and potentially also due to measurement error in 1 variable or both variables. Regarding imperfect administration, while an official report (25) from the organization administering the FTC estimated that 3%–5% of eligible persons did not take up the FTC, an independent study (26) suggested a more plausible, much larger (23%) nonuptake of the FTC. Moreover, a nontrivial percentage of ineligible persons erroneously received the FTC. In 2005–2006 and 2006–2007, for example, 4.8% and 3.2% of families were overpaid tax credits designated for families (including the FTC), and they were not required to repay part or all of the overpaid credit (27). The presence of these "counterfactual" participants indicated that a natural experiment on the FTC had occurred, and therefore the influence of the FTC among these participants was of particular interest.

Outcome

Our outcome was SRH at wave 7, treated as a continuous variable ranging from 1 to 5. Information on SRH was collected using the following question: "In general would you say your health is . . .," with the following response categories (codes shown in parentheses): poor (1), fair (2), good (3), very good (4), and excellent (5). Previous studies of tax credit–health (4, 5) and income-health (28) relationships (using SoFIE data) found comparable associations regardless of whether SRH was treated as continuous or ordinal.

Time-invariant confounders and time-varying CAPTs

Potential time-invariant confounding variables included age (years; continuous), sex (2 categories: female, male), ethnicity (5 categories: indigenous Māori, Pacific, Asian, other, New Zealand European), and education (4 categories: no qualification, secondary school, postsecondary school, college degree), on which data were collected at wave 1 baseline using standard questions (20). We considered potential CAPTs to include the 3 determinants of FTC receipt: equivalized total gross annual family income (minus FTC) (New Zealand dollars; continuous), number of dependent children (continuous), and family type (2 categories: 1-parent family, 2-parent family), derived at each wave. (Detailed information on the derivation of these variables is available from the authors.)

Pooled regression analyses demonstrated that each of these 3 variables was predicted ($P < 0.001$) by the total number of years of receiving the FTC at the previous wave and predicted ($P < 0.001$) SRH at wave 7 (results available from the authors). This provided empirical support for the causal relationship hypothesized in Figure 1 and suggested that the 3 variables could indeed be CAPTs. These potential CAPTs define eligibility for the FTC (13), and most persons eligible for the FTC also received it (25, 26). Therefore, these CAPTs should largely capture time-varying confounding in the model (see Figure 1), and the exchangeability assumption of MSMs (9, 10) of no unmeasured (time-varying) confounding may hold. The MSMs also adjusted for SRH at all previous waves to control for health selection and adjusted for FTC receipt at all previous waves to control for treatment history.

Statistical analysis

We first conducted conventional linear regression analyses. We then conducted an MSM analysis, which enabled us to quantify the net influence of stronger adjustment for CAPTs, health selection, and treatment history.

Unadjusted and adjusted linear regression models. We plotted the number of years of receiving the FTC by SRH score at wave 7 and fitted a smoothing curve (available from the authors), finding a linear exposure-outcome relationship. Model 1 was an unadjusted linear regression model estimating the association between receiving the FTC for an additional year (over the 7-year study period) and SRH at wave 7. Model 2a added the time-invariant confounders and the time-varying confounders measured at baseline. While this model adjusted for time-varying confounders at baseline, it was unable to control for CAPTs and also did not account for health selection and treatment history. Both models adjusted for household-level clustering. Model 1 used the 6,897 (99.96%) participants without any missing data on any variable included in the model, and model 2a used the 5,823 (84.4%) such participants.

MSM using unstabilized and stabilized inverse probability of treatment weights. Model 3 was an MSM estimating the ACTE between each additional year of receiving the FTC (over the 7-year study period) and SRH at wave 7, using *unstabilized* inverse probability of treatment weights (IPTWs). We preferred this MSM over an always treat/never treat MSM, because it better accommodated the substantial change in FTC receipt over time and provided a more generalizable estimate (association per additional year rather than, specifically, over 7 years). We computed the unstabilized IPTWs for the exposure to create a pseudopopulation that was exchangeable with the study population within levels of confounders, as described in detail by Cole and Hernán (29). The unstabilized IPTWs were constructed using the time-invariant confounding variables measured at wave 1 baseline, the 3 CAPTs (i.e., equivalized total gross annual family income (minus FTC), number of dependent children, and family type) measured at wave$_{t-1}$, and SRH and FTC receipt measured at all previous waves. The unstabilized IPTWs ranged between 1.00 and 212,875 (see Web Figure 1, available at http://aje.oxford journals.org/, for distribution). We capped the weights at the 1st and 99th percentiles to eliminate extreme outliers (29), which reduced their range to 1.01–1,273. Finally, an MSM was fitted with total number of years of FTC receipt as the exposure and SRH at wave 7 as the outcome, weighted using the unstabilized IPTWs. This model adjusted for measured time-invariant confounders, measured CAPTs, health selection, and treatment history.

Model 4 was an MSM estimating the same causal relationship as model 3 but using *stabilized* IPTWs. We stabilized the previously calculated unstabilized IPTWs to improve the precision of the MSM (29). The stabilized IPTWs ranged between 0.03 and 368 (see Web Figure 2 for distribution). When capped at the 1st and 99th percentiles (29), they ranged from 0.08 to 6.33. As with model 3, we fitted an MSM with the total number of years of FTC receipt as the exposure and SRH at wave 7 as the outcome, adjusted for time-invariant confounders, CAPTs, health selection, and treatment history. Both MSMs adjusted for household-level clustering and used the 4,014 (58.2%) participants without any missing data on any variable at any wave (exclusions were largely due to missing income data at 1 or more waves; see Web Table 1 for characteristics of excluded participants). The IPTWs were computed and the MSM models fitted using the GENMOD procedure of SAS Enterprise Guide, version 9.3 (SAS Institute, Inc., Cary, North Carolina), computer software (see Web Appendix 1 for SAS code).

Sensitivity analysis. The MSMs necessarily used only the 58.2% of participants with complete data on all waves. Selection bias may have occurred if the FTC-SRH association differed between all participants and only those with complete data. To assess possible selection bias, we compared results from the adjusted regression analysis conducted on 84.4% of participants (model 2a) with those from the same analysis rerun on the 58.2% of participants with complete data (model 2b), expecting different results if selection bias occurred.

RESULTS

Sample characteristics

Table 1 shows the characteristics of the study sample of 6,900 participants at wave 1 baseline according to the total number of years of FTC receipt over the 7-year study period. Of the sample participants, 15.4% were not in a family at wave 1 but were included due to their being in a family in subsequent waves. Most participants (71.4%) did not receive the FTC over the 7-year study period. Between 5.1% and 6.8% of participants received the FTC for 1–3 years, and 1.8%–3.6% received it for 4–7 years. Initial survey nonresponse in SoFIE was 77% (20), and attrition in the study sample was 26.3% (30) (Figure 3).

Unadjusted and adjusted linear regression models

The unadjusted linear regression model (model 1 in Table 2) suggested that each additional year of receiving the FTC was associated with a small, statistically significant ($P < 0.001$) decrease in SRH at wave 7 ($\beta = -0.033$ unit, 95% CI: −0.047, −0.019; central estimate equivalent to 3.7% of 1 standard deviation (SD) of SRH). The adjusted linear regression model (model 2a) found a smaller but still statistically significant decrease in SRH ($\beta = -0.026$ unit, 95% CI: −0.041, −0.010; 2.9% of 1 SD of SRH).

MSMs using unstabilized and stabilized IPTWs

The MSM using unstabilized IPTWs (model 3 in Table 2) also found a small average decrease in SRH at wave 7 stemming from each additional year of FTC receipt ($\beta = -0.039$ unit, 95% CI: −0.058, −0.020; 4.3% of 1 SD of SRH). The MSM that used stabilized IPTWs (model 4) confirmed the small average decrease in SRH at wave 7 ($\beta = -0.031$ unit, 95% CI: −0.050, −0.007; 3.4% of 1 SD of SRH). These estimates of the ACTE were similar to the measure of association from the conventional regression analyses, suggesting no bias from lack of adjustment for potential CAPTs, health selection, and treatment history in conventional regression analyses.

Table 1. Baseline Characteristics of the Study Sample According to Number of Years of Receiving the New Zealand Family Tax Credit ($n = 6{,}900$), Survey of Family, Income and Employment, 2002

Characteristic	No. of Years of Receiving the Family Tax Credit																Total No.
	0		1		2		3		4		5		6		7		
	No.[a]	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	
Total	4,932	71.5	360	5.2	471	6.8	438	6.3	249	3.6	156	2.3	126	1.8	168	2.4	6,900
Age group, years																	
19–24	159	49.5	51	15.9	36	11.2	39	12.1	9	2.8	12	3.7	6	1.9	9	2.8	321
25–34	1,002	55.9	153	8.5	204	11.4	186	10.4	90	5.0	54	3.0	48	2.7	54	3.0	1,791
35–44	1,950	71.4	117	4.3	174	6.4	162	5.9	114	4.2	72	2.6	54	2.0	87	3.2	2,730
45–54	1,548	87.6	36	2.0	57	3.2	45	2.5	30	1.7	18	1.0	15	0.8	18	1.0	1,767
55–64	273	91.0	6	2.0	6	2.0	9	3.0	6	2.0	0	0.0	0	0.0	0	0.0	300
Sex																	
Female	2,709	69.7	195	5.0	279	7.2	261	6.7	150	3.9	108	2.8	81	2.1	102	2.6	3,885
Male	2,223	73.8	165	5.5	192	6.4	177	5.9	99	3.3	48	1.6	45	1.5	63	2.1	3,012
Ethnicity																	
Māori	540	61.0	57	6.4	78	8.8	87	9.8	45	5.1	18	2.0	27	3.1	33	3.7	885
New Zealand European	3,777	74.4	270	5.3	306	6.0	285	5.6	159	3.1	108	2.1	69	1.4	105	2.1	5,079
Pacific	213	61.7	12	3.5	27	7.8	33	9.6	12	3.5	6	1.7	24	7.0	18	5.2	345
Asian	282	66.7	18	4.3	39	9.2	27	6.4	21	5.0	24	5.7	6	1.4	6	1.4	423
Other	126	73.7	3	1.8	15	8.8	9	5.3	6	3.5	3	1.8	3	1.8	6	3.5	171
Highest level of education																	
No qualification	807	67.3	66	5.5	87	7.3	81	6.8	54	4.5	33	2.8	30	2.5	42	3.5	1,200
Secondary school	1,233	66.9	108	5.9	147	8.0	123	6.7	72	3.9	51	2.8	48	2.6	60	3.3	1,842
Postsecondary school	1,911	73.1	141	5.4	168	6.4	168	6.4	93	3.6	48	1.8	36	1.4	51	1.9	2,616
College degree	981	79.2	45	3.6	69	5.6	63	5.1	27	2.2	24	1.9	12	1.0	18	1.5	1,239
Family income[b]																	
Missing data	792	73.7	90	8.4	90	8.4	63	5.9	27	2.5	12	1.1	0	0.0	0	0.0	1,074
Quintile 1 (lowest)	513	44.1	84	7.2	117	10.1	117	10.1	78	6.7	72	6.2	66	5.7	117	10.1	1,164
Quintile 2	609	52.1	84	7.2	123	10.5	123	10.5	90	7.7	54	4.6	42	3.6	45	3.8	1,170
Quintile 3	876	75.1	42	3.6	90	7.7	90	7.7	36	3.1	21	1.8	9	0.8	3	0.3	1,167
Quintile 4	1,029	87.9	45	3.8	42	3.6	36	3.1	9	0.8	0	0.0	6	0.5	3	0.3	1,170
Quintile 5 (highest)	1,116	95.9	18	1.5	9	0.8	12	1.0	6	0.5	0	0.0	0	0.0	3	0.3	1,164

Table continues

Sensitivity analysis

When the adjusted conventional regression model was refitted with only the participants included in MSM analyses ($n = 4{,}104$; model 2b in Table 2), the strength of the association with SRH was −0.031 unit (95% CI: −0.049, −0.014), similar to the model 2a ($n = 5{,}823$) finding of −0.026 unit (95% CI: −0.041, −0.010). Thus, there was no evidence of selection bias due to missing data.

DISCUSSION

Summary of findings

This study found that each additional year of receiving an unconditional tax credit for families marginally decreased SRH among adults in New Zealand. Both conventional linear regression models (estimating associations unadjusted for potential measured CAPTs) and an MSM (estimating ACTEs more fully adjusted for potential measured CAPTs) suggested a statistically significant small reduction in SRH from the tax credit. The size of the association was too small to be clinically meaningful (cutoff 0.25-unit change in SRH) (31), but over a population it might be considered nontrivial. No evidence was found for any net bias from the 3 CAPTs. Most likely, the association of exposure at wave$_t$ with CAPTs at wave$_{t+1}$ (arrow C in Figure 1) was too weak to "activate" sizeable bias. Additional research is required to determine the strength and direction of each CAPT's confounding and mediation pathways. Guidance for when MSMs are actually necessary is needed.

Relationship to previous studies

To our knowledge, no previous study has examined the association between cumulative receipt of a financial credit and health. We previously reported results from a fixed-effects

Table 1. Continued

Characteristic	No. of Years of Receiving the Family Tax Credit																Total No.
	0		1		2		3		4		5		6		7		
	No.[a]	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	
Family type																	
Not in a family[c]	795	74.9	87	8.2	87	8.2	60	5.6	24	2.3	9	0.8	0	0.0	0	0.0	1,062
1-parent family	498	57.2	45	5.2	84	9.7	87	10.0	57	6.6	42	4.8	27	3.1	30	3.4	870
2-parent family	3,645	73.3	231	4.6	300	6.0	291	5.9	165	3.3	105	2.1	99	2.0	138	2.8	4,974
No. of children in family																	
0	1,689	83.3	105	5.2	108	5.3	78	3.8	36	1.8	12	0.6	0	0.0	0	0.0	2,028
1	1,248	69.7	111	6.2	129	7.2	132	7.4	78	4.4	51	2.8	30	1.7	12	0.7	1,791
2	1,380	70.9	90	4.6	150	7.7	108	5.5	87	4.5	39	2.0	39	2.0	54	2.8	1,947
3	504	59.4	45	5.3	60	7.1	93	11.0	27	3.2	33	3.9	33	3.9	54	6.4	849
4–10	114	38.4	12	4.0	27	9.1	30	10.1	21	7.1	21	7.1	24	8.1	48	16.2	297
Self-rated health[d]																	
Poor	72	66.7	6	5.6	12	11.1	6	5.6	3	2.8	3	2.8	3	2.8	3	2.8	108
Fair	264	64.2	21	5.1	36	8.8	39	9.5	18	4.4	15	3.6	6	1.5	12	2.9	411
Good	1,053	68.3	99	6.4	99	6.4	99	6.4	75	4.9	42	2.7	27	1.8	48	3.1	1,542
Very good	1,962	72.6	138	5.1	177	6.5	168	6.2	81	3.0	57	2.1	54	2.0	66	2.4	2,703
Excellent	1,590	74.6	96	4.5	147	6.9	123	5.8	66	3.1	39	1.8	33	1.5	36	1.7	2,130

[a] All numbers of participants in this table are rounded to the nearest multiple of 3 and a minimum value of 3, as per Statistics New Zealand confidentiality protocols.
[b] Equivalized total gross annual family income (minus the Family Tax Credit) in New Zealand dollars (NZ$). Quintile 1: <NZ$23,534; quintile 2: NZ $23,534–NZ$37,671; quintile 3: NZ$37,672–NZ$50,999; quintile 4: NZ$51,000–NZ$73,669; quintile 5: >NZ$73,669.
[c] Note that 15.4% of the sample were not in a family at wave 1, but they were included in the sample due to being in a family in subsequent waves.
[d] Data on self-rated health were missing for 3 participants.

regression analysis looking at change in eligibility status for the FTC and the amount of additional income derived from the FTC, respectively (4). Neither becoming eligible for the FTC nor a $1,000 increase in the amount of FTC that a participant's family was eligible for was associated with changes in SRH, at least in the short term (5). The present study differed from the previous study in that it assessed the cumulative association with the FTC (over a period of 7 years), as opposed to short-term associations (over the course of 1 year). The present study also focused on actual receipt of the FTC, as opposed to eligibility for the benefit. Despite these differences, the estimates from both studies were small in size, suggesting little change in SRH from the unconditional tax credit.

Limitations

MSM estimates are only unbiased under the 5 assumptions specified above (9, 10). In our study, the exchangeability assumption may have been violated, since treated and untreated persons may not have been fully comparable. For example, prospective parents who were unaware of the FTC were more likely to be expecting their first child (as opposed to later children) and more likely to reside in deprived areas than those who knew about the FTC (26). In addition, residual confounding from unmeasured variables (e.g., personality type, fertility) may have occurred.

Positivity was probably not violated on theoretical grounds, considering that the imperfect administration of the FTC resulted in eligible participants' not receiving the FTC (25, 26) and ineligible participants' erroneously receiving the tax credit (27). Formal diagnostics for identifying structural violations (or near-violations) of the practical positivity assumption in MSMs that use exposures measured at 2 or more time points are currently being developed but are not yet available (Dr. Maya L. Petersen, University of California, Berkeley, personal communication, 2015). Our informal investigation of practical positivity identified a small number of potential violations, suggesting a low risk of bias (Web Appendix 2, Web Figure 3).

Consistency was probably not violated, since treatment variation was likely irrelevant. For example, variation in the amount of FTC received seems irrelevant, because even small amounts of additional income from financial credits can considerably influence social outcomes (1, 21, 22). Model(s) misspecification may have occurred, since we treated SRH as continuous rather than ordinal despite the potentially unequally spaced response categories of SRH (32). However, previous SoFIE studies suggested that such bias was probably small, if any (4, 5, 28). Furthermore, misspecification from including continuous variables as simple linear terms rather than flexible terms (e.g., splines) may have occurred. The assumption of no measurement error may have been violated. In a validation study, survey participants underreported their receipt of financial credits (33), suggesting the risk of measurement error in the exposure. Although difficult to estimate, this bias was probably small and, if nondifferential and independent, acted towards the null.

Furthermore, SRH has several well-documented limitations (34) that may have introduced measurement error in the

Table 2. Change in Self-Rated Health (on a 5-Unit Scale) According to Total Number of Years of Receiving the New Zealand Family Tax Credit, Survey of Family, Income and Employment ($n = 6{,}900$), 2002–2009

	Change in Self-Rated Health per Additional Year of FTC Receipt[a]									
	Model 1[b] (*n* = 6,897)[c]		Model 2a[d,e] (*n* = 5,823)[f]		Model 2b[d,e] (*n* = 4,014)[g]		Model 3[h,i] (*n* = 4,014)[g]		Model 4[i,j] (*n* = 4,014)[g]	
	β	95% CI	β	95% CI	β	95% CI	β	95% CI	β	95% CI
Total no. of years of receiving FTC	−0.033[k]	−0.047, −0.019	−0.026[l]	−0.041, −0.010	−0.031[k]	−0.049, −0.014	−0.039[k]	−0.058, −0.020	−0.031[m]	−0.050, −0.007
Intercept	3.943[k]	3.916, 3,970	4.638[k]	4.473, 4.802	4.549[k]	4.350, 4.748	4.023[k]	4.011, 4.034	4.002[k]	3.981, 4.023
Sex										
Female			−0.016	−0.061, 0.029	−0.022	−0.075, 0.030				
Male (referent)			0.000		0.000					
Age, years			−0.013[k]	−0.017, −0.010	−0.012[k]	−0.016, −0.008				
Ethnicity										
Māori			−0.137[l]	−0.213, −0.060	−0.129[l]	−0.218, −0.041				
Pacific			−0.272[k]	−0.395, −0.149	−0.223[l]	−0.369, −0.077				
Asian			−0.342[k]	−0.460, −0.225	−0.310[k]	−0.450, −0.170				
Other			−0.231[m]	−0.424, −0.038	−0.244[m]	−0.483, −0.005				
New Zealand European (referent)			0.000		0.000					
Highest level of education										
No qualification			−0.324[k]	−0.411, −0.237	−0.301[k]	−0.394, −0.209				
Secondary school			−0.159[k]	−0.234, −0.084	−0.141[k]	−0.221, −0.061				
Postsecondary school			−0.152[k]	−0.223, −0.081	−0.125[l]	−0.207, −0.043				
College degree (referent)			0.000		0.000					
Family income[n]			0.013[k]	0.007, 0.018	0.011[k]	0.006, 0.017				
No. of dependent children			0.003	−0.023, 0.029	0.018	−0.014, 0.050				
Family type										
1-parent family			−0.169[k]	−0.246, −0.092	−0.125[m]	−0.220, −0.029				
2-parent family (referent)			0.000		0.000					

Abbreviations: CI, confidence interval; FTC, Family Tax Credit; IPTWs, inverse probability of treatment weights.

[a] Self-rated health could range from 1 (poor) to 5 (excellent).

[b] Model 1: unadjusted linear regression model.

[c] Participants without any missing data on the exposure and the outcome measured at wave 7.

[d] Models 2a and 2b: fully adjusted linear regression models.

[e] Results were adjusted for time-invariant confounders measured at wave 1 baseline (age, sex, ethnicity, and education) and confounders affected by prior treatment measured at wave 1 (family income, number of dependent children, and family type).

[f] Participants without any missing data on the exposure, the outcome measured at wave 7, and the time-invariant confounders and confounders affected by prior treatment measured at wave 1.

[g] Participants without any missing data on any variable measured at any wave.

[h] Model 3: marginal structural model with unstabilized IPTWs.

[i] Results were adjusted for potential time-invariant confounders measured at wave 1 (age, sex, ethnicity, and education), confounders affected by prior treatment measured at each wave (family income, number of dependent children, and family type), treatment history (FTC receipt measured at each wave), and health selection (self-rated health measured at each wave) using IPTWs.

[j] Model 4: marginal structural model with stabilized IPTWs.

[k] $P < 0.001$.

[l] $P < 0.01$.

[m] $P < 0.05$.

[n] Equivalized total gross annual family income (minus the FTC) in New Zealand dollars (NZ$), scaled at NZ$10,000.

outcome. Additionally, if the FTC-SRH association increased with additional years of FTC receipt, the potentially relatively larger associations that may have appeared beyond the 7-year study period were not captured. Finally, if participants who left the SoFIE study differed from those who remained with respect to the receipt of FTC and SRH, the current study may have been influenced by selection bias. However, attrition in this study was comparable with that in similar studies (20) and nondifferential (30). Our sensitivity analysis provided no evidence of selection bias from missing data.

Generalizability

The findings of this study can be generalized to the general New Zealand resident population of adults in noninstitutionalized households. It can also be generalized (with some uncertainty) to comparable populations in other high-income countries with a similar social policy context.

Implications for theory, policy, and research

This study does not support the theory (4, 5, 7) that financial credits improve SRH cumulatively over time. Rather, it provides modest support for the theory (35) that financial credits may not improve individual- and population-level SRH or equity in SRH. Additional research is required to establish which of the several hypothesized causal pathways between financial credits and SRH (1) are active and in which direction they operate to produce no association.

The World Health Organization (36) and other experts (37, 38) have recommended using financial credits as policy tools for addressing the social determinants of health (primarily income) in order to improve population health and health equity. However, the findings of this study suggest that the association between unconditional tax credits and SRH may be small or nil, at least among adults in high-income countries. Additional research is required to assess the potential impact of other financial credit interventions (e.g., cash transfers that are conditional (39) or that address climate change (40)) and other cumulative measures of tax credit receipt (e.g., total dollar amount received) on SRH and other health outcomes. Conducting MSMs alongside conventional regression analyses can provide important insights into the presence and magnitude of bias from potential CAPTs in studies that investigate the cumulative health associations of financial credits or other social interventions, although improved guidance for researchers as to when MSMs are likely to be warranted seems justified.

In conclusion, this study found that receiving an unconditional tax credit for families for an additional year statistically significantly—but only modestly—reduced the cumulative association with SRH among adults in New Zealand. The estimated associations from conventional regression models unadjusted for CAPTs and ACTEs from MSMs adjusted for CAPTs were similar, providing no evidence of any bias from CAPTs.

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