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Informing policy priorities using inference from life satisfaction responses in a large community survey

Christopher P. Barrington-Leigh* and Jan T. Wollenberg†

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N.B. An error in our original publication has been corrected in this version, without a formal correction with ARIQ, so far. The correction relates to the quantitative values of compensating differentials. The changes are for the most part relatively small, and have no qualitative implications for our findings. The latest version of this paper is always at
http://alum.mit.edu/www/cpbl/publications/Barrington-Leigh-Wollenberg-ARIQ2018.pdf

Abstract

Self-reported, quantitative, subjective measures of well-being, such as satisfaction with life overall, are increasingly looked to as measures of public welfare. While this trend is visible at the international and national government levels, regional initiatives and local communities are particularly important in seeking meaningful measures of the quality of human experience and of the success of local policies. Unlike other approaches in which well-being or progress indices are constructed using arbitrary or expert-generated weights on various domains of life experience, subjective well-being can be used to evaluate empirically the relative importance of specific measurable conditions and experiences in supporting a good life. Using a new, large community well-being survey carried out across the U.S. state of Connecticut, we use this method to evaluate the relationship between life satisfaction and a range of other socioeconomic circumstances and conditions. In support of a broad existing literature, we find enormous effects of security and social engagement as compared with variations in income. We then proceed to consider the prevalence of different socioeconomic conditions, in addition to their relative importance to affected individuals, to make inferences about the benefit-costs of feasible state and local policies. There remain some conditions, like social trust and the perceived responsiveness of local government to the needs of residents, which appear very important to well-being but for which the relationship with targeted resource allocation requires further investigation or policy experimentation.

Keywords: life satisfaction; subjective well-being; community well-being; social welfare; policy prioritization; USA

*Corresponding author. Institute for Health and Social Policy, McGill University, Montreal.
†Department of Geography, McGill University, Montreal.

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1 Introduction

In this paper, we use a new, large, and comprehensive community well-being survey in the U.S. state of Connecticut to analyze the ways in which policies targeting a variety of social and economic factors might impact life satisfaction. Use of self-reported life satisfaction to aggregate across domains of human experience has become increasingly prominent. Our approach is based on one increasingly used by economists, psychologists, and policy makers. In this approach, a single, specific survey measure — individuals' self-reported overall satisfaction with life (SWL) — is used as the basis of statistical analysis to evaluate the relative influence of a set of life circumstances on overall human experience, or well-being. In the present case, the variation underlying this evaluation comes from cross-sectional differences across individuals, who are asked both to cognitively evaluate and aggregate their all-encompassing experience of life, as well as to respond to a series of other narrower or more objective questions about the conditions and events in their lives.

A broad literature assesses the interpersonal, inter-cultural and inter-linguistic comparability of cognitive life evaluations (e.g., Helliwell et al., 2010; Exton et al., 2015; Lau et al., 2005; Clark et al., 2005; Diener et al., 2013) and summarizes the relationships between SWL and life circumstances (e.g., Frey and Stutzer, 2002; Dolan et al., 2008; Helliwell and Barrington-Leigh, 2010). Measures of subjective well-being more generally, and SWL in particular, have taken on more prominent roles in measures and conceptions of well-being and social progress for communities, cities, regions, and nations (Barrington-Leigh and Escande, 2018; Barrington-Leigh, 2016; OECD, 2013; Stone et al., 2014; Stiglitz et al., 2009; Cameron, 2010; UK Office of National Statistics, 2011; Bernanke, 2010; Helliwell et al., 2012, 2013, 2015; Global Happiness Council, 2018; Hall et al., 2011). There is an increasing interest in the use of measures of subjective well-being and life satisfaction to inform policy decisions, including the use of life satisfaction data as a kind of 'yardstick' to allow options across very different policy domains to be ranked (Donovan et al., 2002; Dolan and White, 2007). Here, we develop a model to analyze the ways in which a variety of social and economic factors impact life satisfaction and apply the model to rank social priorities in Connecticut.

Our work builds on three existing strands in the literature, referenced above. One is the extensive set of studies contributing to the ongoing project of characterizing, isolating, and quantifying the contributions of different supports of well-being. Much of this work consists of a variance accounting exercise, such as ours, in which causation is apportioned among correlated predictors through rather straightforward regression models. A much smaller component of this literature manages to isolate a single and unidirectional influence though the identification of plausibly independent and external events. A second literature addresses, increasingly practically, the public policy implications of what has been learned from subjective well-being (e.g., Layard, 1980, 2006; Easterlin, 2013; Helliwell, 2011; Ng and Ho, 2006). Third, possibly because of the relative ease with which smaller jurisdictions can innovate both in surveying and in policy experimentation, there is a literature on community-level well-being measurement and applications.

We find strong effects on well-being from several conditions experienced by respondents. Other studies already explore some of these factors in broader populations, including the importance of health care (e.g., Ngamaba et al., 2017), avoiding unemployment (e.g, Helliwell and Huang, 2014; Blanchflower et al., 2014), social trust (Mikucka et al., 2017, among many others), food security (Frongillo et al., 2017), and good government responsiveness (Radcliff and Shufeldt, 2016; Esaiasson et al., 2017; Altman et al., 2017). Where comparable, i.e. for trust and unemployment in particular, our findings are consistent with past studies.

Here we analyze a particularly extensive community-level data set, and innovate in the policy literature by considering the case when individual attributes can be dichotomized, i.e. when problems can be thought of as being discretely solved at the individual level. For instance, individuals may be said to suffer from unemployment or not, and to meet a criterion of food security or not. When socioeconomic conditions for individuals can be expressed in this fashion (or at least on a discrete scale), and when costs of helping those affected can be estimated, benefit-cost analysis can be expressed in a particularly simple form (in comparison, e.g., to O'Donnell and Oswald, 2015). Through the use of life satisfaction data, costs of different kinds of policy outcomes can be made commensurable.

2 Methods

2.1 Survey Design

The Datahaven Community Wellbeing Survey is conducted via in-depth interviews with Connecticut residents and focuses on topics including physical and mental health, economic opportunity, housing, transportation, and civic engagement (DataHaven 2016). The survey design draws from national and international well-being surveys to allow for comparisons between Connecticut and other national and global data such as Healthy People 2020 (`https://www.healthypeople.gov`). On behalf of DataHaven, in 2015 the Siena College Research Institute (SRI) surveyed 16,219 residents of the state of Connecticut. Surveys were conducted from April 1 through October 1, 2016. Residents aged 18 and older were interviewed in English or Spanish in all 169 towns in Connecticut. In our analysis we use inverse sampling probabilities provided by Datahaven in order to weight observations to achieve population estimates. These weights reflect both stratification in the sampling process and post-stratification using the census and the National Health Interview Survey; the latter provides estimates of the distribution of land-line and cell telephone ownership. Stratified sampling and the post-stratification weighting were both carried out separately for land-line and cell-phone based surveys, which were then merged, with appropriate calculation of final weights. See the link above for a more detailed description of the sampling methodology and the complete list of survey questions.

2.2 Modeling Life Satisfaction

Linear regression was used to estimate a model for predicting life satisfaction among Connecticut residents using household income, household size, self-reported physical health, self-reported mental health, and several personal experience variables. The model includes individual level variables, county indicator ("dummy") variables to absorb variation from unmeasured county-level determinants, and cluster dummy variables which grouped observations across 5 clusters based on neighbourhood income, housing density, and poverty rate at the town level. Sampling weights were used to make population estimates in all analyses performed. In our "baseline" model, standard errors are assumed to be orthogonal across individuals. In our "cluster" model, standard errors are estimated by clustering observations across the 5 town-level clusters. Including cluster dummy variables also accommodates unknown variation across these groups, at the risk of a downward (conservative) bias in our estimates.

We model the life satisfaction (LS) of individual i in county j and cluster k as:

$$LS_{ijk} = b_0 + b_I \ln\left(HH\,income_i\right) + b_2 \cdot X_i + \delta_j^{county} + \delta_k^{cluster} + \upsilon_k + \varepsilon_i \tag{1}$$

Where X_i is the vector of the life experience variables for individual i, δ_j^{county} is a constant particular to county j, $\delta_k^{cluster}$ is a constant particular to cluster k, υ_k is an error term common across clusters, and ε_i is the respondent idiosyncratic error term.

2.3 Variable Construction

Table 2 presents the means and variances of our key variables. Life satisfaction responses on a 5-point scale were rescaled from 0 to 100 with a value of 100 for respondents who reported being completely satisfied with their lives overall and 0 for those who stated that they were not at all satisfied. The model controls for age based on 4 groups (18-34, 35-49, 50-64, 65+) as well as marital status. Log income represents the natural logarithm of the midpoint of the reported household income bracket, except for the highest bracket of >$200k, which was coded as ln(200,000); the log form of household income was used in accordance with standard practice to account for diminishing marginal benefits of increased income (Deaton, 2008). All other explanatory variables were rescaled to a 0 to 1 range to allow regression coefficients to be more easily interpreted. These include a measure of overall health, self-rated in five categories from "poor" to "excellent," and a measure of mental health, for which respondents rated the frequency of feeling "down, depressed, or hopeless" again in five categories, from "never" to "very often".

Both dichotomous and multi-level "life experience" variables were created to examine the effects of a variety of personal experiences addressed by the survey (table 1). For the *"Receive needed healthcare"* variable, those interviewed who stated that at some time during the past 12 months they did not get the medical care they needed were classified as lacking healthcare and coded 0. Those who did not report lacking needed care were coded 1; it should be noted, however, that individuals coded 1 may simply

Variable	Possible responses
Receive needed healthcare	Y/N
Have health insurance	Y/N
Food secure	Y/N
Have help (friends/relatives to count on)	Y/N
Employment	Y/N
Adequate transport	Y/N
Volunteered (within past 12 months)	Y/N
Attacked or victim of vandalism/theft (within past 12 months)	Y/N
Walkability (self-percieved availability of sidewalks and services/points of interest within walking distance)	4 levels
Neighbourhood safety (self-perceived safety of walking at night)	4 levels
Trust in neighbours (self-perceived)	4 levels
Ability to influence local government (self-perceived)	4 levels
Responsiveness of local-government to needs of residents (self-perceived)	4 levels

Table 1: Dichotomous (Yes/No) and non-dichotomous (4 level) personal experience variables

not have needed any medical care during the past 12 months, rather than necessarily having received care when they needed it. For the *"Employment"* variable, respondents who stated that they had not had a paid job in the last 30 days but would like to work were classified as unemployed and coded 0. Others, coded 1, were either employed, did not want to be working (e.g., retirees), or may have been unable to work. A detailed description of the variable construction is available in the supplementary material.

2.4 Compensating differentials

Because it is more familiar to conceptualize how a given increase in household income might improve the life satisfaction of a typical adult, we calculated income-equivalent effect sizes for each of the effects included in the model. These metrics (table 3) are often called compensating differentials because they describe how much income could fall while still leaving life satisfaction unchanged if another variable improves, or *vice versa* (e.g., if trust decreases, how much must income rise in order to leave life satisfaction the same as before? See Helliwell and Barrington-Leigh, 2011). Compensating differentials were thus calculated for each of the variables in the model as follows:[1]

[1] To formalize the idea of compensating differentials for changes in a discrete, or indicator, variable X_i, note that the coefficient b_i in (1) represents an estimate of the discrete change ΔLS resulting from a unit change in X_i. From the verbal definition of compensating differential, $\Delta LS = 0$ if $\Delta(\log I)b_I + \Delta X_i b_i = 0$, where I is household income, and b_I is its coefficient in (1). Writing $\Delta(\log I) = \log(I_2) - \log(I_1)$, then, choosing to express the income differential as a compensation in response to a unit *decrease* in X_i, the definition becomes $\log\left(\frac{I_2}{I_1}\right) b_I = b_i$, or $\frac{I_2}{I_1} = \exp\left(\frac{b_i}{b_I}\right)$. The fractional change in income is $\frac{I_2 - I_1}{I_1} = \exp\left(\frac{b_i}{b_I}\right) - 1$, which we refer to as the compensating differential.

$$\text{Comp. differential}_i = \exp\left(\frac{b_i}{b_I}\right) - 1$$

The compensating differential for a given variable thus represents the equivalent fractional rise in income required to generate an equivalent improvement in life satisfaction. For instance, a compensating differential of 0.7 for access to transport would indicate that a 70% increase in income generates, on average, the same improvement in life satisfaction as having access to reliable transport.

3 Results

According to our estimates, a variety of life experience variables are significantly related to self-reported life satisfaction. In Table 3, raw coefficients are presented from the models ("baseline" model without clustering and "cluster" model with clustering based on 5 clusters defined in terms of income, density, and poverty rate) explaining differences in life satisfaction among 9, 340 respondents for whom all variables were available (although 16 223 people were surveyed, not all respondents provided an answer for each question). The coefficient for each variable can be interpreted as the predicted average increase in life satisfaction when the life experience variable improves from 0 to 1. For example, the coefficient of 3.8 for the "health insurance" variable indicates that having health insurance is predicted to increase life satisfaction by 3.8 out of 100. Similarly, if an individual seeking employment can find a job, it is predicted to increase life satisfaction by 5.4 out of 100.

As expected, physical and mental health were strong predictors of life satisfaction. The coefficient of 18.3 for health indicates that moving from "poor" to "excellent" health is predicted to increase life satisfaction by 18 out of 100. Similarly, moving from having very often felt down, depressed, or hopeless in the past month to never feeling down, depressed, or hopeless is predicted to increase life satisfaction by 25 out of 100. These findings are consistent with those of Flèche and Layard (2017) who found that, costs and feasibility aside, protecting mental health would yield the largest improvement in well-being among a variety of measured factors including employment, income, and physical health.

The estimated coefficient on log income, 2.3, implies that going from the lowest ($\ln(7500) = 8.92$ to the highest ($\ln(200000) = 12.21$) income category accounts for an increase of 7.5/100 ($(12.21 - 8.92) \times 2.3 = 7.5$ on the life satisfaction scale. The estimated benefits from improving health or one of the other life experience variables in the model either exceed, or are of comparable size, to the effect of traversing the entire income range. Compensating differentials for the life experience variables were larger than one for most variables tested. The trust in neighbours variable, for example, has a compensating differential of 6.2; moving from strongly disagreeing that those in an individual's neighbourhood can be trusted to strongly agreeing that they can be trusted is associated with the same predicted increase in life satisfaction as a more than 7-fold

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	Mean	Std. Dev.	Min	Max	Observations
Life satisfaction (100 scale)	73.6	23.2	0	100	9.239
Household income (ln)	11.1	0.97	8.9	12.2	9.239
Household size	3.10	1.57	1	7	9.239
Health	0.71	0.25	0	1	9,239
Mental health	0.78	0.26	0	1	9.239
Health insurance	0.96	0.21	0	1	9.239
Receive needed healthcare	0.93	0.25	0	1	9.239
Food secure	0.89	0.32	0	1	9.239
Trust neighbours	0.79	0.30	0	1	9,239
Have help	0.95	0.23	0	1	9.239
Employed	0.95	0.23	0	1	9.239
Transport	0.9	0.29	0	1	9.239
Volunteer	0.47	0.50	0	1	9.239
Walkability	0.53	0.36	0	1	9.239
Influence on local-government	0.34	0.30	0	1	9,239
Responsiveness of local-government	0.48	0.30	0	1	9,239

Table 2: Descriptive statistics

increase in household income. Similarly, even after controlling for household income, the compensating differential for food security was 3.4, suggesting that ensuring an individual is food secure might generate the same predicted increase in well-being as a 4-fold increase in household income.

Such large compensating differentials must be approached with caution, particularly as they reach values close to the total variation in income measured across the survey sample. In such cases, directly interpreting the various effects in terms of income becomes strained, as the large coefficients represent an extrapolation that is outside the variation that is well covered by the data. In addition, the accuracy of large compensating differentials is challenged by the difficulty of finding enough comparable individuals who differ only by income across such a large range. That is, the sample is unlikely to include many residents with incomes both <\$30K and >\$200K who all lack insurance, don't trust their neighbours, don't have access to reliable transport, etc.

Our results are thus more reliable for marginal effects around the mean; the compensating differential of 27 for "government responsiveness" indicates that the effect on life satisfaction of feeling that local-government is responsive to the needs of residents is equivalent to a 28-fold increase in income. We cannot reliably estimate what it means to increase an individual's income by a factor of 28, since such a change is usually accompanied by a variety of changes in one's social conditions. The estimated compensating differentials for mental and physical health are even larger. The larger compensating differentials in 3 also come with large standard errors, reflecting that the

	Regression coefficients		Compensating differentials	
	Baseline	Cluster	Baseline	Cluster
	(1)	(2)	(3)	(4)
Household income (ln)	**2.3**†	***2.3***		
	(.52)	(.71)		
Household size	.15	.15	.067	.067
	(.23)	(.34)	(.11)	(.17)
Health	**18.3**†	**18.3**†	10^3	10^3
	(1.37)	(1.43)	(10^4)	(10^4)
Mental health	**25.2**†	**25.2**†	10^5	10^5
	(1.40)	(1.67)	(10^5)	(10^5)
Food secure	**3.4**⋆	***3.4***	3.4	3.4
	(1.20)	(1.09)	(3.0)	(3.5)
Employed	**5.4**⋆	*5.4*+	9.3	9.3
	(1.65)	(2.2)	(9.8)	(16.3)
Have help	2.3	2.3	1.71	1.71
	(1.53)	(1.38)	(1.95)	(1.97)
Receive needed healthcare	***4.3***	***4.3***	5.3	5.3
	(1.94)	(1.33)	(5.2)	(3.6)
Health insurance	***3.8***	***3.8***	4.1	4.1
	(1.74)	(1.03)	(4.5)	(4.5)
Trust neighbours	**4.6**†	*4.6*+	6.2	6.2
	(1.28)	(1.70)	(5.4)	(1.75)
Volunteer	***1.19***	1.19	.67	.67
	(.60)	(.76)	(.46)	(.78)
Transport	1.22	1.22	.70	.70
	(1.34)	(1.45)	(1.03)	(1.28)
Walkability	***2.0***	**2.0**⋆	1.41	1.41
	(.85)	(.35)	(.99)	(.45)
Influence on local-government	***2.7***	2.7	2.2	2.2
	(1.24)	(1.82)	(2.1)	(2.1)
Responsiveness of local-government	**7.7**†	***7.7***	26.6	26.6
	(1.07)	(1.91)	(23.7)	(46.3)
Constant	***−15.1***	*−15.1*+		
	(5.9)	(5.5)		
R^2**(adj)**	.32	.32	.32	.32
obs.	9083	9083	9083	9083

Significance: **0.1%**† **1%**⋆ ***5%*** *10%*+

Table 3: Raw regression coefficients predicting life satisfaction and associated compensating differentials. Standard errors were adjusted for 5 clusters in cluster model. Standard errors for compensating differentials were calculated using the Delta method.

data do not support quantitative interpretation of these ratios. Instead, we can interpret these effects as being "overwhelmingly large" in comparison to the relatively small effect of income. Indeed, a main finding for these data is that certain life experience variables are enormously important as compared with simple material income changes.

4 Discussion

Measuring life satisfaction can help policy makers by demonstrating the various benefits in terms of wellbeing that are associated with different allocation decisions (Dolan and Metcalfe, 2012). If costs associated with different interventions can also be assessed, life satisfaction data can be used as a sort of "yardstick" to allow interventions to be ranked across very different policy domains (Donovan et al., 2002; Dolan and White, 2007). Here, as highlighted by Dolan and Metcalfe (2012), we use expected gains in life satisfaction from different policy areas to evaluate which forms of spending would lead to the largest increases in life satisfaction.

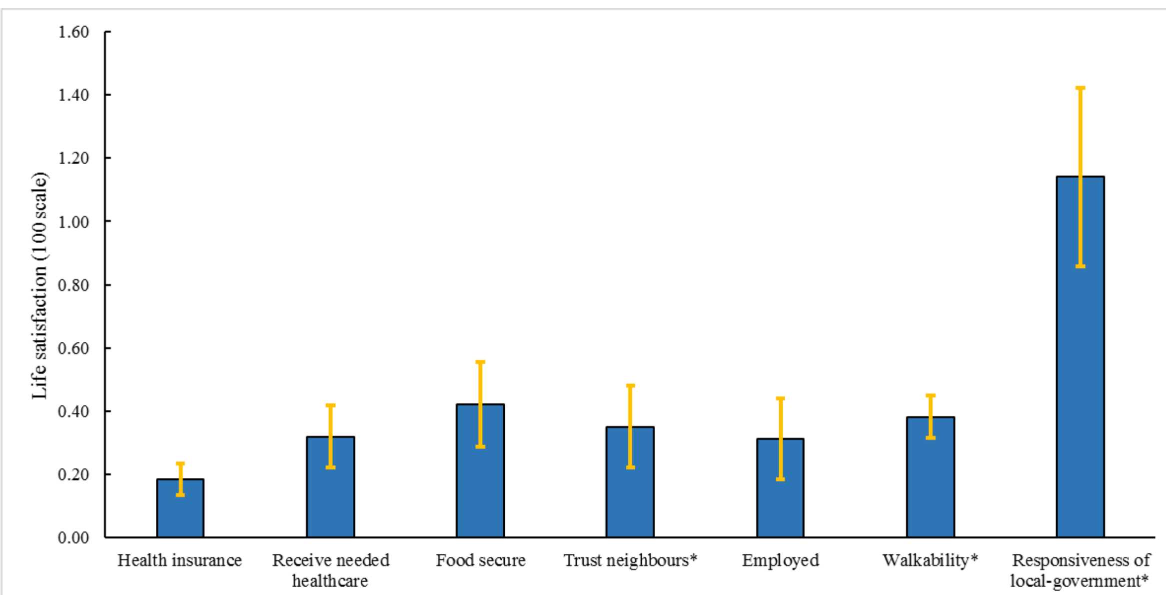
When improvements are made to life experience variables, the aggregate increase in life satisfaction at the population level depends on both the strength of the effect for a given individual (table 3) as well as the number of individuals within the population that would be affected by the change. The Community Wellbeing Survey provides insight into the proportion of Connecticut's population that struggle with issues such as food insecurity and unemployment, so by multiplying the compensating differentials by the corresponding proportion, decision-makers can evaluate the net impact of these hardships at the "whole population" level. This utilitarian approach has the obvious drawback, however, that it treats changes to different individuals as equally valuable. For instance, it values a benefit to an impoverished person no more than the same benefit going to someone already affluent or well taken care of. In addition, it assigns little weight to rare problems, even if they are severe for the individuals involved. Yet, despite this blindness to inequality, average life satisfaction is an aggregate metric of increasing prominence, and it puts emphasis on human experience more than other aggregate indices, such as gross domestic product, which are oriented towards economic productivity and performance.

We computed weighted proportions among survey respondents for the dichotomous life experience variables which were significantly correlated with life satisfaction (table 4). The total number of Connecticut residents in each category was calculated by multiplying each proportion by the 2016 population estimate for Connecticut (US Census Bureau 2017). The aggregate benefit of improving each of the various social and economic conditions at the population level was then computed for each variable by multiplying the relevant coefficient by the proportion of residents affected (figure 1).

Interestingly, this analysis demonstrates that just because an improvement in a life experience has a strong predicted effect on individual life satisfaction, it may not have a strong influence statewide. For example, interpreting our coefficients causally, providing food security to the estimated 443 387 (12.4% - based on the proportion in the

	Fraction (survey)	Connecticut residents
No health insurance	0.0489	174,889
Lack needed healthcare	0.0744	266,088
Lack trust	0.0763	272,883
Food insecure	0.124	443,838
Unemployed	0.058	207,148
Low walkability	0.1910	683,102
Feel local-government is not at all responsive to	0.148	529,315

Table 4: Population distribution per life experience variables



*Represents the increase in mean life satisfaction for moving only those with the lowest level (of trust, walkability, or responsiveness) to the highest level (i.e. from a score of 0 to a score of 1).

Figure 1: Aggregate increase in mean life satisfaction (across entire population) for improving various life experience variables. Error bars represent standard errors for coefficients from the cluster model (i.e. with clustering).

survey) Connecticut residents who reported being food insecure would increase mean life satisfaction in Connecticut by 0.42 out of 100, while ensuring that the 207 148 residents of Connecticut who wanted to work could find employment would increase mean life satisfaction in Connecticut by 0.31 out of 100. Thus, although the relative impact on life satisfaction of food insecurity (coefficient of 4.0) is less than that of unemployment (coefficient of 5.4), the aggregate benefit of providing food security is higher due to the larger number of individuals who report being food insecure. Similarly, although walkability has a low compensating differential, a fairly large percentage of Connecticut residents (19%) live in neighborhoods with very low walkability metrics, so improving walkability also would be likely to make life better for many people in the state.

Naturally, costs associated with these types of improvements are also likely to scale with the number of people affected. Yet, total costs also depend on whether the conditions to be improved are individual or collective in nature. For example, the cost of providing health insurance is likely to scale nearly linearly with the number of individuals who are uninsured, while the cost of improving non-rival or public goods, such as trust or social capital, may scale weakly (as trust begets trust). These types of analyses are thus likely to have surprising implications in cost-benefit calculations when the conditions to be changed are collective, rather than individual, outcomes.

5 Policy Implications

Our analysis suggests that life satisfaction depends on a variety of factors in an individual's social context. Compensating differentials are large for almost all life experience variables, indicating that income support alone may not be the most cost-efficient way to improve well-being at the population level. For example, the compensating differential for food security of 3.4 suggests that a 400% increase in income would be required to yield the same improvement in well-being as ensuring that an individual feels food secure. Using the median household income for Connecticut (2011-2015 in 2015 dollars) of $70 331 (US Census Bureau 2016), in dollar terms the compensating differential for food security is $295 390 year^{-1}. In comparison, the USDA's low-cost food plan estimates a national average monthly cost of $638.50 (as of March 2017) to provide a nutritious diet for a family of four (USDA 2017); food security could thus be provided at an annual cost of $7 662 per household, which is only a small fraction of the compensating differentials above. In addition, $7 662 represents the annual cost of the household's entire food budget, and it is likely that a smaller amount would be required to ensure that the household remained food secure.

Using the coefficients estimated here (table 3), it is thus possible to compare the cost of increasing mean life satisfaction by improving different social and economic conditions. For example, given the coefficient of 3.4 for food security, assuming the cost of providing food to a food-insecure household is 7662$ year^{-1}, the annual cost per one point increase in life satisfaction would be 2254$ year^{-1} (7662$ / 3.4). A similar calculation could be made for employment; a program designed to provide wage support for new employees in non-profit organizations, for example, could allow organizations to create jobs and employment that would not otherwise have been available. Each job created could thus potentially allow an individual to move from being unemployed to employed. Assuming the government provided 100% of an employee's salary at the Connecticut minimum wage ($10.10 per hour), the annual program cost would be approximately $21,000 per new job. Based on the employment coefficient of 5.4, the annual cost per one point increase in life satisfaction would thus be approximately $3889 year^{-1}, again only a fraction of the compensating differential.

The data presented here suggest that the built environment also plays an important role in life satisfaction. Moving from the lowest to the highest walkability score is predicted to increase life satisfaction by 2.0 out of 100 for the average survey respondent; these findings are consistent with other studies which have shown positive associations between neighbourhood walkability and quality of life (Jaśkiewicz and Besta, 2014). These results are particularly surprising given that Connecticut is a place where many people choose to live in suburban areas with fewer places to walk to and 83% of people drive their own car to work. Thus, although it might be costly or difficult to modify the walkability of existing neighbourhoods, our findings indicate that enhancing walkability should remain a priority when planning and constructing new residential developments.

Quantifying the cost of improving some of the other life experience variables tested is more difficult; it is unclear, for example, how much it would cost (or whether it is even possible) to ensure that everyone can trust their neighbours. Yet, the positive impact of improving social capital is clear and policies should be designed to encourage the development of increased social capital within communities. Similarly, the perceived responsiveness of local-government to the needs of residents emerged as a strong contributor to improved life satisfaction with a predicted increase in life satisfaction of 7.7 out of 100 for the average survey respondent who moves from feeling that local-government is "not at all" responsive to the needs of residents to feeling that the government's responsiveness is "excellent". Similarly, the high compensating differential of 27 suggests that adults who are connected to and trusting in the place where they live are more likely to be satisfied with their lives. Given that only 10% of Connecticut residents reported feeling that government responsiveness is "excellent", our results suggest that it would be possible to increase mean life satisfaction in Connecticut by nearly 2% if even just half of the population felt that the responsiveness of local government was "excellent".

Previous studies have also shown that the quality of government strongly dominates per capita incomes as a determinant of life satisfaction (Helliwell and Huang, 2008). Our results show that in addition to the quality of the government, the perceived responsiveness of government to the needs of residents emerged as the single most important experience variable explaining differences in life satisfaction (excluding physical and mental health). Given that governments and public organizations often have goals which are difficult to quantify, measuring the responsiveness of the public sector as perceived by citizens is thus one option for measuring government performance (Vigoda, 2000). Initiatives designed to improve engagement between government and local citizens could likely improve overall life satisfaction at relatively low cost.

6 Conclusions

Our results, and particularly the high compensating differentials, suggest that it is important to consider social support systems in a more nuanced way than simply using income support alone. Where available, cost estimates for improving various social and economic conditions could be used in conjunction with regression coefficients to compare the costs and benefits associated with improving life satisfaction through a variety of different policy measures. These estimates could be used to rank social priorities in Connecticut and to identify which types of changes can generate the largest aggregate improvements in life satisfaction at the lowest cost.

Increasing families' incomes across the board would be a costly endeavor. However, improving the safety net for those most impacted by financial hardships, and improving community conditions like access to nutritious food, health care, neighborhood cohesion and walkability, and relationships with different levels of government may be more easily attainable, and falls within the purview of state and local governments. These new analyses provide a starting point by identifying some of the potential improvements with the greatest "bang for their buck" as well as ones that reach the broadest populations.

Our work represents a small step in the cautious ongoing task of bringing human-centered outcomes into the process of policy evaluation and prioritization. Based on the broader literature, we expect our qualitative findings to be generalizable to other jurisdictions, but the specific challenges to well-being will vary with populations and policy environments. Our work gives an example of the kind of inferences possible when a large ($\sim$16,000) sample is taken in a single state or region. Grounded in data that represent a diverse cross-section of the state, these types of analyses can help decision-makers make Connecticut a better place for everyone to live.

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A Supplementary Material

Variable construction:

Health insurance: Respondents who reported that they did not have any kind of health insurance were coded 0. Those who had insurance were coded 1.

Food secure: Survey respondents who reported that there was a time in the past 12 months that they did not have enough money to buy food that they or their family needed were classified as food insecure and coded 0. Those who never reported lacking money to buy the food they needed were classified as food secure and coded 1.

Have help: Those who stated that they did not have friends or relatives they could count on for help if needed were coded 0. Those who stated that they did have people to count on for help if required were coded 1.

Transport: Respondents who stated that there was a time in the past 12 months when they wanted to go somewhere but stayed home because they had no access to reliable transport were coded as 0; those who did not report a lack of adequate transport were coded 1.

Volunteer: Respondents who stated that they had not volunteered with an organization to address needs in their community over the past 12 months were coded 0; those who had volunteered were coded 1.

Attacked or vandalized: Respondents who stated that they had either been attacked, threatened, or had someone deliberately vandalize or try to steal their property were assigned a value of 0. Those who responded no were assigned a value of 1.

Non-dichotomous variables

Walkability: A neighbourhood walkability score was calculated for each respondent based on the following two statements pertaining to pedestrian accessibility and safety:

- Many banks, stores, markets, or places to go are within walking distance (10 to 15 min) of my home;
- There are safe sidewalks and crosswalks on most of the streets in my neighborhood.

Responses were coded into four levels from 0 to 1 for both statements (1 (strongly agree); 2/3 (somewhat agree); 1/3 (somewhat disagree); 0 (strongly disagree)). The average of the two responses was taken to determine the "walkability" score, thus yielding a score of 1 for someone who strongly agreed with both statements and a value of 0 for someone who strongly disagreed with both.

Trust in neighbours: Coded into four levels from 0 to 1. A value of 1 was assigned to respondents who stated that they strongly agree that people in their neighbourhood can be trusted and a value of 0 was assigned to those who strongly disagreed (0 (strongly disagree); 1/3 (somewhat disagree); 2/3 (somewhat agree); 1 (strongly agree)).

Influence on local-government: The self-perceived ability to influence local government decision making was coded into four levels from 0 to 1. A value of 1 was assigned

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to those who felt they had great influence and 0 to those who felt they had no influence at all (1 (great); 2/3 (moderate); 1/3 (little); 0 (none)).

Responsiveness of local-government: The self-perceived responsiveness of local government to the needs of residents was coded into four equal levels from 0 to 1. A value of 1 was assigned to those who felt that responsiveness was excellent and a value of 0 for those who felt it was poor (1 (excellent); 2/3 (good); 1/3 (fair); 0 (poor)).

Neighbourhood safety: The perceived safety variable was constructed based on the response to the question "I do not feel safe to walk in my neighbourhood at night". A value of 1 was assigned to those who strongly disagreed that they felt unsafe (i.e. they felt safe) and 0 to those who strongly agreed that they felt unsafe (1 (strongly agree); 2/3 (somewhat agree); 1/3 (somewhat disagree); 0 (strongly disagree))

Cluster dummy variables: We use a set of five similarity group indicators in the "Cluster" variation of our baseline model. These indicators simply identify the five different values of the "ct5" variable provided by DataHaven. These five groups are based on a k-means similarity grouping algorithm used to group census tracts into five groups based on their mean income, population density, and poverty rate. Additional details are available from DataHaven.