O Brother How Art Thou: Propensity to Report Self-Assessed Unmet Need

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Research investigating self-assessed unmet need (SUN) has taken the reports from surveys as given and subsequently attempted to discover patterns in inequality of access to healthcare. This requires the yet untested assumption that, given a certain level of care and demand, the likelihood of reporting unmet need does not vary across socio-economic status (SES), be satisfied. Using an administrative dataset spanning 2001 to 2011 comprised of sufferers of a set of conditions that suggest unmet need (n=3,300) we evaluate the proposition that, given health status and care received, the propensity to report unmet need does not vary along SES. The results are further validated using the Canadian Community Health Surveys between 2001 and 2013 (n=237,483). We find that the assumption of independence between reporting SUN and SES is not satisfied. Many of the groups found to have less access in previous studies may simply be more prone to interpret/answer the survey questions about unmet need in a certain way. The results of this research suggest that, in its present incarnation, survey data on self-assessed unmet need does not accurately measure what much of the academic literature has assumed it does.

Introduction

Health care access based on *need* is the foundation of an equitable health care system. If a gap exists between the services received and the appropriate level of care for one's illness, the individual is said to have an *unmet* health care need. To ensure fair access to health care services in a horizontal equity sense (those with the same needs for healthcare are treated equally), policy makers require accurate measures of unmet need to identify and remove barriers to necessary care. A common approach in the literature is to use self-assessed unmet need (SUN), which represents an individual's belief that they experienced a health issue that was unaddressed or under-addressed. SUN is generally established by a yes/no survey question and may differ from an objective or *true* unmet need: whether the person in question is receiving the appropriate care in the appropriate amount or not. When SUN is used to investigate inequities in health across socio-economic subgroups (SES) (such as income quantiles, race, or gender), conclusions based on the results will capture both the subjective experience with health care and the objective component of access. SUN, therefore, is a function of true unmet need (objective component) and some error in its observation in the data which may or may not be idiosyncratic (subjective component).

If SUN is to be used as a measure of inequity of access, it must meet two criteria. First, SUN must have some empirical link to future health outcomes (i.e. lack of access needs to have meaningful consequences for health). This relationship was established using Canadian data in Gibson et al. (2019) (with similar results being seen in France (Dourgnon et al. 2010), and specific subpopulations in China (Zhen et al. 2015)). Second, differences in the subjective part of SUN that do not relate to actual experiences in the healthcare system should not vary systematically over the categories through which researchers examine inequalities. If the subjective component of SUN varies systematically by SES, spurious correlations could be found in studies attempting to understand access. This spurious correlation would suggest an improper redistribution of resources to target populations based on an overstated level of SUN relative to unmet need. For example, if individuals with high levels of education are found to report higher levels of unmet need but are also more likely to report unmet need given health and care received, then redistribution that aims to satisfy their perceived health care requirements is likely to be a misallocation of resources. Interesting findings by Legal and Vicard (2015) using French survey data show that changing the order and specific wording of questions (without changes to the spirit of the questions being asked) can result in large changes (in some cases 6-12 percent) in the reporting rates. This work suggests that the probability of reporting SUN is quite sensitive to the individual's interpretation and that we might expect to find that differences in interpretation exist across SES that will meaningfully impact the reporting rates. None of this is to suggest that researchers interested in the subjective experience of healthcare provision from the patient perspective should be averse to using SUN, although these researchers should be mindful that there is an important health-related component to SUN that needs to be addressed in such research.

The purpose of this paper is to identify any differences in the subjective parts of SUN. Our research is guided by the following question: Are there important patterns in the likelihood of reporting self-assessed unmet need that would make it unsuitable for examining equity of access across socio-demographic groups? To answer this question, we conduct two analyses using a unique dataset that links the Canadian Community Health Survey (CCHS) with hospital discharge records from the public sector in Canada. First, looking at a subset of respondents who were hospitalized for ambulatory care sensitive conditions (ACSC), we compare the mean rates of SUN between SES. Hospitalization for an ACSC generally represents true unmet need; hence, a reporting-gap between two subgroups (e.g. males and females) would signal a difference in opinion about the appropriateness of care received. Second, we define a prediction error as the difference between observed SUN in the data and a predicted value of SUN based on a propensity score estimation and examine its distribution across different socio-economic groups. We find evidence that the inequality suggested by certain subpopulations' higher rates of SUN can partly be explained by differences in interpretation or response to the inherently subjective survey questions about unmet need. This suggests the need for testing and refinement of the unmet need question with an aim to generate more consistent reporting between groups.

Unmet Need

Unmet need is a broad term that reflects the difference in care received and the care required to treat one's illness. According to Chen and Hou (2001), an unmet need is the result of problems with at least one of three aspects of health care delivery, namely the accessibility, the acceptability, and the availability of treatment. Inappropriate levels of care arise for a myriad of reasons and may fall in one of five categories of unmet need, as outlined in Allin et al. (2010) (see table 1). These categories distinguish between those who do not receive any care, either by choice or failure of the health care system, and those who receive treatment that is inadequate. Unmet need could be misreported in any of these categories through either a false positive (SUN is reported while unmet need does not exist) or false negative (there is an unmet need, but no report of SUN). For many of these categories, differences in perspective will generate a different responses across individuals.

Previous studies using SUN as a measure of unmet need have found that those with low income, higher levels of education, women, and recent immigrants have higher rates of unmet need (Koolman 2007; Ähs and Westerling 2006; Shi and Stevens 2005; Newacheck et al. 2003; Chen and Hou 2001; Himmelstein and Woolhandler 1995). These studies have taken reports of SUN as given and could be incorrect if a response bias operates in opposition to the identified patterns in access.

In the CCHS, SUN is established via a yes/no response to the question ``During the past 12 months, was there ever a time when you felt that you needed health care but you/he/she did not receive it?" (Statistics Canada, 2012, p.17). A "yes" response to this question will prompt further questions about the reason/type of unmet need. An important question is whether the biases we might observe in SUN will be expected in other surveys of this nature. The European Union's EU-SILC: question PH-040 asks about the unmet need for medical examinations or treatments. While the EU-SILC is administered in many languages, the coding of the response in the survey gives some indication of the intent of the question wording. For the affirmative, the response is coded as "Yes, there was at least one occasion when the person really needed examination or treatment but did not receive it". The time frame (12 months) is identical to the time frame used in the measure in this paper, and the intent of the question is to assess the access to care in general (Eurostat, 2017, p.271). In the US, questions tend towards a similar wording (see the description of the Survey of Older Americans in (Cohen et al. 1997)). The key difference between the Canadian and EU/American wordings lies in the word 'feel' present only in the Canadian survey which may elicit a *more* subjective response to the question other surveys' prompts. Furthermore, macro differences in culture and healthcare systems would suggest that this exercise should be repeated using data from the EU and US to ascertain whether disparities exist in these surveys. Finally, we again point to Legal and Vicard (2015) to highlight that seemingly insignificant differences in wording and survey design can have strong impacts on the rate of reporting SUN.

Theoretical Framework

Since the amount of need will obviously depend on the individual's health status, the following discussion of population use, care and expectation levels should always be assumed to be conditional on health.

Suppose that the expectations for care are distributed over number of visits for the general population with distribution $f(n)$. For a given level of care n, all those whose expectations for care are greater than n will report SUN (i.e. $\int_n^\infty f(n)\,dn$ corresponding to a percentage $(1-(F(n)))$). Unmet need studies have assumed that the difference in reporting rates for unmet need are driven by the differences in access (ie. differences in n) and not by differences in expectations, i.e. differences in $f(n)$. Suppose in contrast, a subpopulation has a different distribution of expectations $g(n)$ from that of the general population that is first order stochastically dominated by $f(n)$. For an illustrative example, we plot expectations which satisfy a chi squared distribution with different means in figure 1.

For a given a level of care $\hat{n}$, share $1-F(\hat{n})$ of the general population will feel that this level of care is inadequate and share $1-G(\hat{n})$ of subpopulation j will feel the level of care is inadequate. With the assumptions about the subpopulation we made in defining $G(n)$ pictured in figure 1, we should observe a higher percentage of the subpopulation with SUN.

[F1: HERE]

We note that the marginal person who is reporting unmet need (the person whose expectations are exactly $\hat{n}$) has a higher expectation of care and thus a higher level of observed care than those with expectations $<\hat{n}$. This model is consistent with the findings of Hurley et al. (2008): that those with a system-related unmet need had higher than expected healthcare utilization; although we are quick to remind the reader that their findings are not *necessarily* driven by differences in expectations.

In any study of imperfect access, we note that the observed level of care and the desired level of care are not always the same. We can think of SUN as being a function of the desired level of care. SUN is not reported if the desired level n is less than or equal to the observed level $\hat{n}$ satisfying equation (1) for individual i of SES j:

$$\hat{n}_{ij} \geq n_{ij}. \tag{1}$$

On the other hand, SUN is reported if the expected level is greater than the observed level (when inequality (1) does not hold). We cannot observe n_{ij} directly and thus we require an assumption to proceed. Suppose, consistent with the utilization literature, that the population average expectation of care ($E[n]$) is a function of health (h) only (i.e. preferences are independent of SES). We can thus replace n_{ij} with $f(h_{ij}) + \epsilon_i$ where ϵ_i is a random disturbance. In this case, the decision to report SUN becomes:

$$SUN_i = \mathbf{I}\left(f\left(h_{ij}\right) + \epsilon_i > \hat{n}_{ij}\right), \tag{2}$$

where $\mathbf{I}()$ is the indicator function taking value one if the argument is true and zero otherwise. In expectation this should not vary with j conditional on h_{ij} and $\hat{n}_{ij}$. If ϵ is correlated with SES, however, equation (3) should be rewritten as:

$$SUN_i = \mathbf{I}\left(\epsilon_{ij} > \hat{n}_{ij} - f\left(h_{ij}\right)\right). \tag{3}$$

SUN will now be seen to vary with SES, conditioning on health and observed care, since membership in group *j* is a partial determinant of the error term. Within this framework, we attempt two exercises. First, we condition on a value of $\hat{n} - f(h_{ij})$ that has been deemed unsatisfactory by a health authority, and attempt to test whether ϵ_{ij} has a different mean from $\epsilon_{i,-j}$(where the subscript -*j* denotes observations outside of SES *j*). Second, we attempt to describe the distribution of $\epsilon_{i,j}$ relative to $\epsilon_{i,-j}$ using a health and care-based predicted value of unmet need.

Empirical Framework

Ambulatory Care Sensitive Conditions

ACSCs are conditions whose appropriate treatment occurs without hospital admission (primary care physician, outpatient clinic, or even in the emergency room). More specifically, the Canadian Institute for Health Information (CIHI) defines ACSC as conditions where ``...appropriate ambulatory care could potentially prevent the onset of this type of illness or condition, control an acute episodic illness or condition, or manage a chronic disease or condition." A disproportionately high hospitalization rate is presumed to reflect problems in obtaining access to appropriate primary care." (Couris et al. 2011). We propose that a hospitalization for an ACSC reflects an unmet need for primary care where either the quality or amount is insufficient. This would be categorized as SUN type 4 (see table 1), where experts feel that the type of care received is inappropriate and is the only true positive that exists in the unmet need framework that is observable in the data, since it is the only category that relies on external criteria.

Given that the people in question are still receiving care (our ACSC patients have been admitted to an acute care facility) the reports of SUN will contain some true negatives and some true positives. Our identification assumes that the number of false positives is near-zero and the rate of false-negative reports is very high in this group (though our argument only requires that they not appear differentially across the groups). The nature of these conditions does not eliminate the possibility that some of these hospitalizations are truly unavoidable and that no unmet need exists.

With these assumptions, comparing the mean rates of SUN between two groups and finding a reporting-gap would suggest that there is some difference in beliefs or expectations that leads one group to report SUN at a lower rate. This reporting rate differential, if and where it exists, provides a new way to look at the average rates of SUN. For example, if women and men tend to report SUN at the same rate in the general population, yet one group is found to underreport in the ASCS analysis, we may be concerned that there exists an access problem between men and women that was unseen just by taking the rates of SUN as representing true unmet need. Within the theoretical model, this will test whether, for a level of $\hat{n}$ that is below an expert assigned threshold for unmet need, there is a gap between $F(\hat{n})$ and $G(\hat{n})$.

We use two separate definitions of ACSC: the first is from Grignon et al. (2015), and the second directly from CIHI (2014), although many such lists of ACSC conditions exist (see for example Walker et al. (2009), Caminal et al. (2004), and Brown et al. (2001)). A critical issue in studies relying on ACSC is the choice of conditions. As our study aims to examine unmet need through ACSC, our criteria for conditions becomes different from studies seeking to use ACSC as a performance indicator for health systems (e.g. Young et al. (2016)). The most important criterion is that the hospitalization be avoidable given proper primary care; this critically maps into unmet need type 4 - care received is inappropriate. We are less concerned about other criteria sometimes used to choose ACSCs, including the prevalence of the disease (as some exceedingly rare conditions simply will not appear in our sample), and the consistency in diagnostic coding (as our hospitalization records are collected by a single statistical authority.) By CIHI's definition, ACSC are considered only for people younger than seventy-five who have a ``most responsible diagnosis" - the diagnosis, or diagnoses, that led to the patient's admission to the hospital - of an ACSC, we apply these criteria also.

As we have selected our ACSC lists (see table 2) to prioritize cases where there is most likely an unmet need, we should expect to see higher reporting rates of SUN among those with an ACSC hospitalization. What we are interested in is the differential in reporting rates between different SES. If we are to reject the existence of differences in reporting behaviour we should not observe large differences in reporting SUN among our ACSC hospitalized.

We test whether the proportion of people in a particular group who report SUN is greater or less than the proportion in the rest of the population in the direction proposed by past studies (we test according to Chen and Hou (2001) since they are using the same survey during approximately the same time period) to evaluate whether this difference is at least partly explained by propensity to report. For continuous variables (age, income in 2002 dollars) we test whether the mean for those reporting SUN is less than (greater than) the mean for those not reporting.

It could be argued that the results of the analysis are driven not by differences in propensity to self-assess unmet need, but rather by differences in the distribution of diseases between groups even among those with an ACSC. In addition to our two different lists of ACSC, we present a recalculated p-value using only those conditions that cannot predict the socioeconomic variable when used as the lone predictor in a linear probability model ($p>0.05$).

Propensity analysis

To generalize our investigation into differential reporting rates, we first estimate the population average distribution of utilization-standardized unmet need, i.e. we attempt to remove the objective part of SUN:

$$Pr\big(SUN = 1|\hat{n}_{ij}, h_{ij}\big). \tag{4}$$

Using this estimated function, we are able to identify a residual $\hat{\epsilon}_{ij}$ by subtracting $S\hat{U}N$ from SUN_i where $S\hat{U}N$ is the fitted value based on the estimated equation. We then examine the distribution of $\hat{\epsilon}_j$ by regressing the values on socio-economic indicators using the unconditional quantile regression methods of Chernozhukov et al. (2013) (hereafter CFM) with a small modification to permit survey weights. This method identifies differences between subpopulations using counterfactual distributions to compare the quantiles of different socio-economic groups.

Consider two different groups. The distributions of covariates such as immigration or education may not be the same between the two groups, and differences in distributions of $\hat{\epsilon}_j$ and $\hat{\epsilon}_{-j}$ may be partially driven by differences in other observable factors. By using the counterfactual analysis, we isolate the effect of group membership on the distribution of prediction errors. With this method, we are unable to disentangle the different types of potential reporting biases (i.e. our calculated scores can be a composite of any bias that results in a deviation from the population average reporting behaviour).

Equation (4) defines the distribution of SUN given observed healthcare use and health status; the proxy for expectations of levels of healthcare deemed satisfactory. Insofar as these expectations differ from the average expectations of individual groups, the difference between SUN predicted by the model and the individual's report will offer us a metric upon which to examine differences between the various socio-demographic characteristics that may influence the expectations about care. Using this residual, we estimate the effect of various socio-demographic factors on the distribution of the prediction errors. For a given quantile for type *j*, CFM describe three potential counterfactual scenarios: The first counterfactual scenario reflects what we might think of as differences in effects of covariates between groups. The second counterfactual scenario reflects the effect of differences in covariate distributions. For example, suppose that immigrants are disproportionately male, we should expect the effect of immigrant status to influence the propensity both directly (through the effect of being an immigrant), and indirectly (through the increased likelihood of being male). The first counterfactual scenario estimates the direct effect, while the second scenario estimates this indirect effect, considering only the influence of the differences in other socio-economic information between immigrant and non-immigrant estimates. The last counterfactual scenario combines 1 and 2 into a total effect. We are interested in all the counterfactual scenarios in our analysis and will discuss one and two separately. Since the distribution of the residual will be bimodal (with observed minus predicted SUN being positive in cases where the respondent claims to have unmet need, and negative when they do not) we examine the positive values (i.e. those whose survey indicated that they had SUN) only which simplifies exposition without distorting qualitative conclusions.

We estimate equation (4) using the following controls in a probit model: activity restrictions, BMI (where BMI is represented by |BMI-21.8|), age and age^2, type of smoker (daily, occasional, former, never), a comprehensive set of available chronic condition dummies, the natural log of "number of consultations with medical professionals" (i.e. physicians and nurses, but not eye and dental professionals), a dummy for having a regular family doctor, and the set of administrative health region dummies. The specific formulation of the unmet need model was chosen by a cross validation exercise to maximize fit - the specifics of which are available in an online appendix [Link to appendix A].

Following the estimation of the unmet need model, we conduct the decomposition analysis at the deciles of the prediction error. In the CFM methodology, the counterfactual analysis considers the effect of a single binary variable, integrating the distribution of other covariates to develop the `direct' effect. We thus run a separate decomposition for each possible state within a socio-economic variable (instead of being a continuous measure, the respondent's income is categorized in a series of binary variables during the survey and subject to 8 separate decompositions). We test for stochastic dominance and indicate whether the group being analyzed is reporting more (or less) across the distribution of predicted values i.e. the effect of the SES variable is positive at all deciles for those reporting SUN. In the case of actual reports of SUN, stochastic dominance where $QE_X > 0 \forall X$ (where QE_X is the quantile effect at decile X) suggests the situation in figure 1 where the subpopulation assumes the distribution with higher expectations for care (i.e. $G(n)$).

While the analysis described above is able to draw on a large number of individuals, a problem exists in trying to measure a potential response bias using only the self-reported data from the same survey. Extensive research has been devoted to the topic of reporting bias in health surveys regarding self-reported measures of health (see for example Black et al. (2017), Hernàndez-Quevedo et al. (2005), Benìtez-Silva et al. (2004), and Kerkhofs and Lindeboom (1995)) with mixed findings. While we cannot solve the problem of self-report, the propensity analysis provides a way to assess the external validity of our findings for the parts of the population that do not experience an ACSC hospitalization.

Our analysis employs data from the Research Data Centres (RDC), which are all collected from individuals under the understanding that the data can be used for research. The collection of over 30 universities in Canada who host an RDC have deemed that researchers working in one of the centres do not need to seek ethics approvals for their projects.

Data

Our ACSC sample arises from a self-selected group of respondents to the CCHS in 2001, 2003, 2005 and 2007-2011 who agreed to have their survey responses linked to the Discharge Abstract Database (DAD), which contains the hospital discharge records for all hospitals in Canada, excluding Quebec. The DAD provides information on the date of visit, all diagnoses made during the visit, all treatments and procedures performed during the visit, and the patient's status at discharge. For this analysis, we used discharge records for the fiscal years from 1999 to 2011 to link to the CCHS observations. We then match the hospital records for the 12 months prior to an individual's CCHS survey date since the SUN question specifies the last 12 months as a timeframe.

The CCHS covers Canadians age 12 and over (except for institutionalized, military and reserve populations) with stratified sampling meant to adequately sample rare characteristics and small populations. While we exclude individuals with non-response in our outcome or observable measures, this results in a very small reduction in our sample. Since ACSC hospitalizations are very rare, we naturally do not observe many cases where an ACSC hospitalization also coincides with being sampled for the CCHS within one year. Our sample size for the ACSC analysis is approximately 3300 and is not representative of the Canadian population.

Since it is optional for respondents to agree to the administrative data linkage, concern about self-selection biasing our results prompted us to attempt to determine if the linked sample was different than the full CCHS. Further examination revealed that the sample means of our regressor variables were not vastly different from the sample means available in the full CCHS. Thus, we do not find any evidence to suggest that those respondents who agreed to link administrative data were different based on observables in the survey, though we acknowledge that our ACSC sample may suffer from unobservable selection bias.

For the propensity analysis, we expand the set of survey years to include 2012 and 2013, as well as those who did not agree to link their data to the administrative records. We exclude pregnant women in our analysis along with those who are missing data on pertinent questions. Our total sample size for estimation is 237,483.

Results

ACSC Analysis

Table 3 shows the proportions of the socio-economic variables in the ACSC sample and the proportion of each subgroup that reported SUN amongst the ACSC sample. Males made up 45.3 percent of those admitted to hospital with an ACSC, with approximately 13.7 percent of them reported having a SUN. Approximately, 18.6 percent of females hospitalized with an ACSC reported having a SUN. The majority of the sample had at least a high school diploma. The education subgroup with the highest rate of SUN was those with some post-secondary education at 18.8 percent. Of the 3300 admitted to hospital for an ACSC, 11.1% of the sample was born outside of Canada. Both Canadian born and non-Canadian born respondents had approximately 16.4 percent of respondents reporting SUN. Table 4 reports the means for age and income in 2002 dollars. The mean age for those who reported a SUN was 56.1 and the mean for those who did not report SUN was 53.6. Mean income was $41,702 for those with a SUN and $33,556 for those without.

Table 5 presents the results from a one-sided test for a difference in proportions of people reporting SUN across SES. The direction of the inequalities we test are based on those from Chen and Hou (2001). Recall that in our framework, a higher likelihood or reporting means that for a given health profile and care received, one group will report access problems at a higher rate than the other group. A small p-value suggests that the disparities observed in population proportions is driven in part by the higher likelihood of reporting access problems for the group that reports more access problems. A p-value close to 1 indicates that there is likely to be a difference between the two groups' reporting behaviours that would result in an underestimation of the extent of the inequality (i.e. the group that seems to have less access, is also under-reporting their lack of access). Finally, for p-values closer to 0.5, observed differences in access are unlikely to be explained by differences in the likelihood of reporting. Our ACSC analysis suggests men are less likely to report than women; married and common-law couples are less likely to report than non-married couples; widowed, single, and divorced couples are under-reporting SUN; and that propensity to report decreases with income and age. These findings suggest that disparities between men and women are overstated, and disparities found over age and income are understated. Furthermore, we find that there is no difference in reporting behaviour between immigrants and non-immigrants or across education and for single individuals. The findings for males, age and income are robust to the conditions selected, and the findings for the restricted conditions and full list are generally compatible. We note that while there are more significant findings on the CIHI list, half of these conditions are very commonly excluded based on the disparate incidence across categories. Specifically, angina and COPD (where COPD is the most common hospitalization in our sample) are excluded for most of the SES variables. This suggests caution in using the CIHI list, and we have the greatest confidence in the excluded conditions list. We turn to the propensity analysis for further evidence to support these conclusions.

Propensity Analysis

Summary statistics in table 6 show the population statistics of the estimation sample (i.e. with the provided survey weights incorporated). The table shows the overall proportions by SES as well as the proportion of each who report SUN and the average Health Utility Index (HUI3). The HUI3 (Horsman et al. 2003)- is a single number used here as a proxy for health status. Most of the subpopulations have very similar average health by this measure, although there is an obvious (and well established) gradient of higher education correlating with better health. Although statistics for income are not shown, there is a similar trend of HUI3 increasing with income and unmet need decreasing with income. For those with income less than 15 thousand, unmet need is 18%; this falls gradually to 10% at incomes over 50 thousand and is stable thereafter. Since income usually varies with age, these unconditional averages should not be taken at face value.

Table 7 displays the results from the estimation of the propensity score. Our cross-validation exercise results in an out-of-sample pseudo-R^2 of 0.069. While pseudo R^2 is not analogous to OLS' R^2 in that we cannot say that our prediction model explains ≈ 7% of the variation in SUN, the low value does suggest that SUN is not easy to predict using health status as measured by the CCHS, or perhaps using any measure of health status (note that McFadden (1977) describes a fit of 0.2 to 0.4 as excellent). This other potential weakness of SUN as an evaluation metric deserves further scrutiny, however, we will not address it further in this work.

Since the error in the quantile analysis is specified as $SUN(reported) - \widehat{SUN}$, for those reporting SUN only, all the values will be (weakly) positive. The closer the error term is to zero, the closer the expectations of care must be to the population average.

Table 8 presents the results of a conditional quantile regression of our socio-economic variables on the predicted value from the first stage regression of SUN on health variables. This shows that the health statuses that predict SUN are not orthogonal to SES. We should not expect, even given universally equal access to care, that people with different health statuses should fail to obtain care at the same rate. Although not the purpose of the paper, the quantile regression provides some preliminary evidence that baseline SUN reporting rates should be conditioned on health status to properly account for differences in health, and that studies looking at rates of unmet need in a population may be re-establishing the social determinants of health rather than identifying differences in access to care.

We observe that trends in reporting behaviour seen in table 5 match the predictions of our health and usage regression in table 8, suggesting that health status can predict reporting behaviour. Two exceptions are those who are widowed or separated who report more unmet need than the average despite having predicted probabilities not far from (or even lower than) average. A possible explanation (aside from reporting behaviour) for this could be that this life stage is quite stressful, and yet the CCHS did not ask about (and thus we are unable to condition on) any mental health issues during the study period. With mental health, and other missing health information that might belong in our first stage, unavailable, we introduce the type of unmet need in the decomposition as a sensitivity analysis. This is described at the end of this section. While the comparison of the predictions to the reporting data is promising in terms of understanding broad patterns, a more thorough investigation of the errors in the prediction is needed to determine whether reporting behaviour differs systematically across SES.

The counterfactual distribution analysis can help us make sense of the differences in reporting behaviour across different socio-economic groups (representing the subjective part of SUN). First, we can test whether the direct effect coefficients at the deciles are all negative (positive). This would suggest that a group has lower (higher) expectations of care for all levels of predicted SUN. If this difference is not established, yet there are some deciles where the coefficient is statistically different from zero, this suggests that the propensity to report diverges as reports become more or less likely (i.e. the accuracy of reporting depends on the predicted likelihood of reporting).

The decomposition analysis results are shown in table 9 and in an online appendix. Table 9 shows the effect of coefficients conditioning on the distribution of the other covariates in the analysis. This eliminates the "indirect effect" of differences in the distributions of other factors between any two groups being considered. Table A2 [link to appendix B] shows the indirect effect and gives the expected difference in predictions that arise solely from the differences in the joint distributions of other characteristics. The coefficient in table 9 can be thought of as the effect on the likelihood of reporting because the individual has characteristic 'x'. The coefficients in table A2 represents the effect of the likelihood of reporting, not because the individual has characteristic 'x', but because people with characteristic 'x' are more/less likely to also be 'y', 'z', etc. Both of these coefficients are valuable since the indirect effects are often larger in magnitude than the direct effects, often move in opposite directions, and suggest that some of the inequity in group-average rates of SUN could also be the result of a joint distributional effect rather than a difference in experience between two separate groups. The bootstrap stochastic dominance test we employ follows from Linton, Song, and Whang (2010) where the null hypothesis is that the estimated quantile effect is smaller than (greater than) the counterfactual distribution of quantile effects, e.g. $H_0: QE_x < 0 \forall X$ $H_a: QE_x \geq 0$ for some X. Under this setup it is possible to reject/fail to reject multiple null hypotheses. We report our stochastic dominance results as follows:

Reject	Fail to Reject	We report
$H_0: QE_x < 0 \forall X$, $H_0: QE_x = 0 \forall X$	$H_0: QE_x > 0 \forall X$	$QE_x > 0 \forall X$
$H_0: QE_x > 0 \forall X$, $H_0: QE_x = 0 \forall X$	$H_0: QE_x < 0 \forall X$	$QE_x < 0 \forall X$
$H_0: QE_x < 0 \forall X$	$H_0: QE_x = 0 \forall X$, $H_0: QE_x > 0 \forall X$	$QE_x \geq 0 \forall X$
$H_0: QE_x > 0 \forall X$	$H_0: QE_x = 0 \forall X$, $H_0: QE_x < 0 \forall X$	$QE_x \leq 0 \forall X$

Additionally, if we fail to reject *any* null hypothesis we report "-" since this likely suggests an overlapping distribution. If we reject *all* the null hypotheses, we report S.O.D. (second order dominance); the reader should consult the coefficients to understand whether the group is more or less variable in its reporting than the reference group.

To assist in understanding the magnitudes of the estimated effects, we provide the standard deviation of the outcome in the bottom of each table. Most of the significant direct-effect estimates at the median fall between 10 and 40 percent of a standard deviation of a prediction error. There is no simple analogy or interpretation that demonstrates how this change might affect population reporting rates since population reporting rates also depend crucially on the health of the population - which is factored into the prediction at the first stage. The size of the estimates would suggest that in many cases, the degree of differential behaviour in reporting casts doubts on the validity of intra-group comparisons using SUN.

Table 9 shows a number of differences in the position of the distributions of expectations. Notably, we find that men's reporting behaviour first order stochastically dominates that of women i.e. women are more likely to report. We also find a gradient in reporting behaviour in income with low-income respondents being more likely to report than higher-income respondents (both confirming our most robust findings in the ACSC analysis). While this reporting pattern is somewhat puzzling given the idea that knowledge of the system may be a factor in reporting, it is worth noting that the income decomposition conditions on education levels, and the education pattern is as expected: post-secondary grads more likely to report than other education levels, and those without high school less likely to report than those with at least high school. Black and East-Asian respondents are less likely to report than other racial groups, while Arabs are more likely to report SUN (evidence we cannot provide in the ACSC analysis). The indirect effects shown in the online appendix table [link to appendix B] demonstrate that some differences in average reporting rates in groups are reinforced by indirect effects (such as married, low education, low income), while other groups see attenuation (such as immigrants, blacks, and post-secondary grads). Policymakers attempting to correct the distribution of health-care resources based on reports of unmet need will tend to over-adjust for the former groups and under-adjust for the latter.

An alternative explanation for the results is that the types of unmet need differ across groups, perhaps owing to experiences with the system, health conditions we cannot observe in the first stage (a type of misspecification of the first stage regression), or other socio-economic information we do not control for in the decomposition analysis. If this were the case, we could understand the difference in socio-economic groups as being not the result of reporting bias but genuine differences in experience with the healthcare system. Using these categorizations (i.e. availability, affordability, acceptability), we try to identify whether difference in types of SUN across socio-economic groups might explain the differences in reporting. The details of this exercise can be found in the online appendix [link to online appendix C]. Only one result changes in the direction of less difference (black goes from < 0 to ≤ 0), while several results change in the direction of more significant differences between distributions. South Asians and married move from ≤ 0 to < 0 singles move from " $-$" to ≤ 0 suggesting that in select cases do changes in the distribution of experiences with types of unmet need explain the differences obtained by examining pooled SUN None of these changes affect our conclusions.

Conclusions

We have shown that the propensity to report SUN when asked by a surveyor varies by gender, marital status, income, and gender independently from health. These results have been demonstrated using both internal (to the survey) and external data. Because of these differences in reporting behaviours, we advise analysts to control for these variables when using SUN in estimating models related to health care access. Policy prescriptions generated from the raw data (especially if they do not take differences in distributions of health conditions into account) will inevitably redistribute resources or target care in a way that is inefficient relative to the unmet needs in the population. Of course, if one's goal is to capture the subjective experience of the health care system, it is appropriate to use SUN as long as controls for health and health care services received are included. Given that the conceptualization of unmet need from Allin et al. (2010) admits also that the expectations of quality may differ between the different socio-demographic groups (type 5 - subjective expectations) we cannot rule out that differences in experiences of quality between socio-economic groups could drive our results. Given the question asked in the survey, however, we believe any attribution of a quality dimension to the question to be incorrect - although, this does not mean that the respondents to the survey felt the same way, or that inequities in quality are not interesting. Future work should focus on ensuring that health surveys more accurately measure unmet need with less non-need related variation between subpopulations. Until this time, researchers should understand that the unmet needs they are measuring are often endogenously determined by the SES they are trying to map them to.

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Tables

Table 1 - Categories of Unmet Need

Cat.	Name	Description	Example	Unmet Need Report
1	Unmet-unperceived	Subject does not know they need care	Undiagnosed cancer	No
2	Subjective chosen	Knows of need, but elects not to seek care	Taking advil for chronic migraines	Maybe
3	Subjective not chosen	Attempted unsuccessfully to seek care	Very long wait time	Yes
4	Clinician Validated	Care received is inappropriate	Regular emergency visits for chest pain (angina) instead of proper management	Maybe
5	Subjective expectation-based	Good care received, but patient unsatisfied	Patient expects constant attention during hospital stay	Maybe

Adapted from Allin (2010)

Table 2 - ACSC Conditions

Condition	Primary Specification	CIHI
Anaemia	✓	-
Angina	✓	✓
Appendicitis with complications	✓	-
Asthma (adult)	✓	✓
Bleeding or Perforated Ulcer	✓	-
Chronic Obstructive Pulmonary Disease	✓	✓
Diabetes	✓	✓
Diseases of the Upper Respiratory Tract	✓	-
Disorders of hydro-electrolyte metabolism	✓	-
Epilepsy	✓	✓
Gastroenteritis		
Hypertension	✓	✓
Immunization Preventable Diseases	✓	-
Pelvic Inflammatory Disease	✓	-
Pneumonia	✓	-
Skin Diseases		
Tuberculosis	✓	-
Urinary Tract Infection	✓	-

Restrictions apply as per CIHI (2014). We do not observe any hospitalizations for some conditions present in Grignong, Hurley & Wang (2015) these conditions do not appear in this list.

Table 3 - Sample characteristics among CCHS respondents with an ACSC (N=3300)

Characteristic	Proportion (%)	Proportion reporting SUN (%)
Gender		
Male	45.3	13.7
Female	54.7	18.6
Education		
Less than high school	38.4	15.9
High school graduate	14.6	15.8
Some post-secondary	7.4	18.8
Post-secondary grad	39.6	16.7
Immigrant		
Yes	11.1	16.4
No	89.9	16.3
Marital Status		
Married/common-law	53.9	21.2
Widowed/separated/ divorced	24.6	21.4
Single	16.1	16.0

Table 4 – Mean Age and Income among CCHS respondents with an ACSC

Characteristic	Mean Overall	Mean | SUN	Mean| no SUN
Age (Years)	55.6	56.1	53.2
Income ($)	42,360	41,702	33,556

Table 5 - P-Values to Test ACSC SUN Reporting Behaviour (N=3300)

Socio-economic characteristic	Literature inequality direction	P-value all conditions	CIHI conditions	P-value With excluded conditions	Excluded conditions
Gender	Female > male	0.00**	0.00**	0.02**	2,5,8,10, 11, 13, 14, 15, 16, 17, 19
Education:					
Less than high school	Other> l.t.high school	0.35**	0.30	0.33	2,3,10,11,15
High school grad	Other > high school grad > l.t.high school	0.33	0.06	0.54	5,11
Some post-secondary	Post-secondary grad >Some post-secondary >other	0.11	0.00**	0.33	3,7,8
Post-secondary grad	Post-secondary grad>other	0.34	0.65	0.33	1,3,10
Immigrant	Immigrant>non-immigrant	0.53	0.18	0.824	5,7,10,12,17
Marital Status:					
Married/common law	Other > married/common law	0.00**	0.14	0.11	1,2,3,5,17
Widowed/separated/divorced	Widowed/separated/divorced<other	1.00	0.22	0.92	1,3,5,10,11,15,18
Single	Single>other	0.61	0.17	0.17	1,2,3,5,10,11, 15,17,18
Income	Higher income > lower income	1.0	1.0	1.0	3,4,9,10,11,14,17,18
Age	Younger > Older	1.0	1.0	1.0	1,2,3,5,7,8,10,11,12,14,15,17,18,19

**P-value < 0.05, *P-value < 0.10.

1-Anemia, 2-Angina, 3-Appendicitis, 4-Asthma, 5-Bleeding/Perforated Ulcer, 6-COPD, 7-Diabetes, 8-Diseases of Upper Respiratory Tract, 9-Disorders of Hydoelectrolyte Metabolism, 10-Epilepsy, 11-Gastroenteritis, 12-Hypertension, 13-

Immunization Preventable Disease, 14-Pelvic Inflammatory Disease, 15-Pneumonia, 16-Skin Disease, 17-Tuberculosis, 18-Urinary Tract Infection

Table 6 - Summary Statistics

Category	Sample Share of Population	% with SUN	Mean HUI
Male	50.3	9.8	0.89
Female	49.7	12.6	0.87
Immigrant	41.3	11.2	0.89
Non-Immigrant	58.7	11.2	0.87
< High School	21.2	8.3	0.84
High School	17.8	10.2	0.87
Some Post Secondary	7.1	13.6	0.88
Post Secondary	53.9	12.4	0.89
Married	48.2	10.1	0.88
Common Law	10.1	15	0.9
Widowed	4.5	8.9	0.79
Separated	2.5	15.1	0.83
Divorced	4.9	14.6	0.83
Single	29.8	11.2	0.89
White	79.7	11.2	0.88
Black	2.3	12.3	0.88
Arab	1	18.6	0.89
East Asian	7	8.8	0.9
South Asian	3.7	9.1	0.89
West Asian	0.6	12.2	0.89
Latin American	1.4	12.4	0.91
Other Race	4.3	15.5	0.84
Sample population average	-	11.2	0.88

Table 7 - Probit Regression for Predicting SUN

Health Variable	Coefficient	Standard Error
Self-Assessed Health		
Very Good	0.18*	0.02
Good	0.33*	0.02
Fair	0.51*	0.03
Poor	0.68*	0.05
Age	0.03*	0
Age Squared	0.00*	0
BMI[1]	0	0
Smoking		
Occasionally	0.01	0.03
Former	-0.04	0.02
Never	-0.09	0.02
Has regular medical doctor		
Yes	-0.42*	0.02
Unsure	-0.13	0.16
Chronic Conditions	✓	
Health Regions	✓	

1. BMI=|BMI-21.8|

*p-value < 0.05

Table 8 - Conditional Quantile Regression on Predicted Value of First Stage Regression

Socio-Economic Characteristic	Coefficient Q_x=.2	Coefficient Q_x=.8
Marital Status		
Married	-0.005	-0.053
Common Law	0.014	-0.006
Widowed	-0.028	-0.106
Separated	0.005	-0.011
Divorced	-0.001	-0.023
Single	0.001	-0.045
Education		
< High School	-0.007*	-0.026
High School Grad	0.001	-0.009
Some Post-Secondary	0.002	-0.006
Post-Secondary Grad	0.004	-0.007
Income (thousands)		
< 15	0.017*	0.102*
[15-20)	0.01	0.065*
[20-30)	0.007	0.047*
[30-40)	0.005	0.031
[40-50)	0.005	0.019
[50-60)	0.004	0.013
[60-80)	0.005	0.011
≥ 80	0.005	0.001*
Male	-0.003*	-0.017*
White	-0.002*	0.005*
Immigrant	0	0.001

Constant	0.046	0.204

*Coefficient is significantly different from **all** alternative classifications at 5% level

Table 9 - Decomposition Results - Direct Effects for SUN=YES

Characteristic	QE_{10}	QE_{20}	QE_{30}	QE_{40}	QE_{50}	QE_{60}	QE_{70}	QE_{80}	QE_{90}	Dominance Test
Male	-.050*	-.031*	-.026*	-.021*	-.015*	-.013*	-.012*	-.009*	-.006*	$QE_x<0\ \forall\ x$
Income < 15	.136*	.132*	.114*	.092*	.074*	.053*	.041*	.027*	.016*	$QE_x > 0\ \forall\ x$
Income [15-20)	.080*	.061*	.052*	.044*	.034*	.026*	.026*	.022*	0.012	$QE_x > 0\ \forall\ x$
Income [20-30)	.047*	.052*	.043*	.035*	.028*	.021*	0.015	0.008	0.006	$QE_x > 0\ \forall\ x$
Income [30-40)	0.032	0.023	0.017	0.012	0.01	0.009	0.009	0.007	0.003	-
Income [40-50)	0.009	0.007	0.007	0.004	0.002	0.003	0.003	0.002	0.002	-
Income [50-60)	0	-0.002	-0.007	-0.009	-0.006	-0.004	-0.001	0	0.003	-
Income [60-80)	-.050*	-.027*	-.016*	-0.01	-0.005	-0.003	-0.001	0	0.001	$QE_x<0\ \forall\ x$
Income ≥ 80	-.062*	-.044*	-.032*	-.023*	-.018*	-.013*	-.013*	-.007*	-.005*	$QE_x < 0\ \forall\ x$
White	0.004	0.006	0.005	0	0.001	0.002	0.004	0.001	-0.004	-
Black	-.085*	-0.036	-0.026	-0.006	-0.004	-0.018	0.006	0.005	0.007	$QE_x<0\ \forall\ x$
Arabic	0.017	.068*	.065*	.058*	.058*	.048*	.045*	.040*	0.021	$QE_x>0\ \forall\ x$
East Asian	-.112*	-.067*	-.045*	-.027*	-.019*	-.016*	-.013*	-.009*	-0.004	$QE_x<0\ \forall\ x$
South Asian	-.060*	-0.034	-0.016	-0.015	-0.009	-0.001	0	-0.004	0.001	$QE_x \leq 0\ \forall\ x$

West Asian	-0.042	-0.058	-0.054	-0.05	-.042*	-.038*	-0.02	-0.014	-0.006	$QE_x \leq 0 \ \forall x$
Latin American	0.076	0.02	0.005	0.017	0.014	0.013	0.017	0.01	0.021	-
Other	.069*	.051*	.035*	0.02	0.009	0	-0.001	0	0.004	$QE_x > 0 \ \forall x$
Married	-0.007	-0.008	-0.008	-0.007	-0.003	-0.004	-0.005	-.006*	-.003*	$QE_x \leq 0 \ \forall x$
Common Law	0.004	0.009	.020*	.020*	.016*	.016*	.017*	.017*	.016*	$QE_x > 0 \ \forall x$
Widowed	-0.073	-.097*	-.089*	-.075*	-.065*	-.057*	-.048*	-.039*	-.031*	$QE_x < 0 \ \forall x$
Separated	0.043	0.033	0.03	0.025	0.017	0.014	0.007	0.003	0.003	
Divorced	.074*	.081*	.066*	.047*	.031*	.017*	.013*	.012*	.008*	$QE_x > 0 \ \forall x$
Single	-.031*	-0.016	-0.01	-0.007	-0.004	-0.005	-0.002	0.001	.004*	
< High School	0.004	0.003	0	-0.003	-0.006	-.008*	-.010*	-.011*	-.007*	$QE_x < 0 \ \forall x$
High School Grad	0.004	0.011	0.009	0.007	0.007	0.007	0.004	0.003	0.002	-
Some Post-Secondary	-0.009	-0.004	-0.002	0.001	-0.003	-0.001	0.001	1	0.003	-
Post-Secondary Grad	-0.02	-0.011	-0.008	-0.007	-0.005	-0.003	0	0.002	0.006	$QE_x \geq 0 \ \forall x$
Immigrant	0.011	-0.002	0.002	0.007	0.006	0.004	0.004	0.005	0.004	$QE_x \geq 0 \ \forall x$
Prediction Error Statistics:	SD	0.137		1st percentile:	0.348		99th percentile:	0.979		

*p-value of quantile effect < 0.05

Appendix A

Description of Estimation of Propensity Equation:

In the estimation of the propensity to report SUN, we considered eight model specifications. Our choice of model specification in order to generate the predicted probability of SUN for our decomposition analysis was based on the model's true error. True error is a measure of the model's inability to fit data points outside the given sample (out-of-sample goodness-of-fit was measured by pseudo-R2 (McFadden 1973) in a k-fold cross validation as described in Daniels (2012) exercise with k=25).

We considered four sets of predictor variables, regressing self-reported unmet need on each set using both the probit and logit estimators (the specifics of the parameterization can be seen in table A1). In our estimation, SUN is modelled as a function of age, health region (the approximately 125 administrative regions for health-care provision in Canada), health, and health care use variables. The control variables for health and health care we consider are: activity restrictions, body mass index (BMI), type of smoker, comorbid conditions, the respondent's health region, age, and province of residence. Activity restriction is a dummy variable which takes a value of 1 if the respondent was unable to do tasks at work, school or home due to health problems (and 0 otherwise). BMI, which is computed as |BMI - 21.8|; 21.8 is the midpoint of a "healthy" BMI, and we do not expect unmet need to simply be a function of increasing BMI, although estimates using other specifications of BMI do not change the results of our study. Type of smoker is a set of four dummy variables: daily, occasional, former (someone who has smoked at least 100 cigarettes in their life but does not presently smoke), and never. Chronic condition dummies in our model include: asthma, fibromyalgia, arthritis, back problem, blood pressure, migraines, COPD, diabetic, heart disease, cancer, ulcers (stomach or intestinal), post stroke, urinary incontinence, bowel disorder, Alzheimer's, chronic fatigue syndrome, multiple chemical sensitivity, mood disorder, and anxiety disorder. To attempt to condition on supply side factors for unmet need, we use a complete set of health region dummies. Observed utilization is measured by the "number of consultations with medical professionals" (e.g. physicians, nurses, but excluding eye and dental professionals), denoted by Q_{md} as well as whether or not the individual has a regular family doctor.

Extension to types of unmet need:

SUN due to access-related reasons is reported more among those in worse health, and SUN for reasons pertaining to acceptability more among those in better health. To evaluate whether these differences are material to the reporting behavior of individuals across the various measures of SES we're looking at. When looking at the covariance between these types and the socio-economic variables we see a variety of patterns emerge. We may be able to partially explain the SUN reports in terms of these differences in types. This would be the case if types of unmet need and prediction error were correlated systematically with the groups that we observe to over(under)-report in the pooled analysis. To examine this, we add "type of unmet need" to our decomposition exercise (see table 11). By adjusting the distribution of types of unmet needs across the observational categories we can examine whether the differences in the experience of unmet need may be driving the differences in observed reporting. In most socio-economic categories the differentials in reporting distributions established earlier do not change between specifications. We reiterate here what is stated in the paper: only one category changes significance in the direction of less difference (black goes from < 0 to ≤ 0), while several categories change in the direction of more significant differences between distributions. South Asians and married move from ≤ 0 to < 0 singles move from ``$-$" to ≤ 0 suggesting that in only a few cases do changes in the distribution of experiences with types of unmet need explain part of the differences obtained by examining pooled SUN. We present the "direct effects" with the set of reasons as additional control variables (thus the distributions of reasons have been accounted for in the direct effects of Table A3.

Online Appendix Tables

Appendix A

Table A1 - In-Sample and Out-Of-Sample Goodness-Of-Fit For Propensity Score Model Specifications

	Model							
	Logit				Probit			
Variable	1	2	3	4	1	2	3	4
X	X	X	X	X	X	X	X	X
Qmd	X	X			X	X		
ln(Qmd)			X	X			X	X
Age^2		X		X		X		X
Goodness-of-fit								
In-sample	0.0923	0.0945	0.0993	0.1015	0.0933	0.0953	0.1002	0.1023
Out-of-sample*	0.0626	0.0636	0.0669	0.0681	0.0632	0.0642	0.0678	0.0687

*Out-of-sample goodness of fit measured as the average pseudo-R^2 from 25-fold cross-validation.

*All models contain health-region fixed effects.

Appendix B

Table A2 -Decomposition Results - Indirect Effects for SUN=YES

Characteristic	QE_{10}	QE_{20}	QE_{30}	QE_{40}	QE_{50}	QE_{60}	QE_{70}	QE_{80}	QE_{90}	Dominance Test
Male	-.009*	-0.004	-0.002	-0.001	0	0	0	0.001	.001*	S.O.D
Income < 15	.023*	.011*	0.005	0.003	0.001	0.001	0	-0.001	-0.002	$QE_x > 0 \ \forall x$
Income [15-20]	.027*	.014*	.008*	0.005	0.002	0	-0.001	-0.002	-.004*	S.O.D

Income [20-30)	.021*	.010*	.007*	.004*	0.002	0.001	0	0	-0.001	$QE_x > 0 \ \forall x$
Income [30-40)	0.008	0.004	0.004	0.002	0.002	0.001	0.001	0	0	-
Income [40-50)	0.005	0.003	0.003	0.002	0.001	0.001	0.001	0	0	-
Income [50-60)	-0.002	-0.001	0	0.001	0.001	0.001	0	0.001	0.001	-
Income [60-80)	-0.006	-0.002	-0.001	0	0	0.001	0.001	0.001	0.001	$QE_x \geq 0 \ \forall x$
Income ≥ 80	-.020*	-0.013	-0.012	-0.007	-0.004	-0.003	-0.002	-0.003	-0.002	-
White	0.002	-0.002	0.002	0.001	-0.001	-0.001	-0.002	-0.001	0	-
Black	.032*	.024*	.016*	.012*	.009*	.008*	.007*	.006*	.004*	$QE_x>0 \ \forall x$
Arabic	0.018	0.015	0.01	0.009	0.007	0.005	0.004	.004*	0.002	-
East Asian	-0.008	-0.005	-0.005	-0.004	-.003*	-0.003	-0.002	-0.002	-0.002	-
South Asian	-0.011	-0.007	-0.005	-0.004	-0.004	-0.003	-0.003	-0.002	-0.001	-
West Asian	-0.015	-0.005	-0.003	-0.002	-0.001	-0.001	0.001	0.002	0.002	-
Latin American	0.007	0.007	0.007	0.005	0.004	0.003	0.003	0.003	0.001	-
Other	.023*	.014*	.010*	.007*	.006*	.004*	.003*	0.002	0.001	$QE_x > 0 \ \forall x$
Married	-.043*	-.023*	-.016*	-.011*	-.009*	-.005*	-.004*	-.002*	-0.001	$QE_x < 0 \ \forall x$

Common Law	-.020*	-.008*	-.008*	-.006*	-.004*	-.003*	-.002*	-.002*	-0.001	$QE_x < 0 \; \forall \; x$
Widowed	.059*	.051*	.038*	.030*	.022*	.016*	.012*	.009*	.004*	$QE_x > 0 \; \forall \; x$
Separated	.044*	.034*	.024*	.018*	.013*	.010*	.008*	.005*	.002*	$QE_x > 0 \; \forall \; x$
Divorced	.053*	.037*	.027*	.020*	.015*	.010*	.008*	.005*	.002*	$QE_x > 0 \; \forall \; x$
Single	.025*	.018*	.013*	.010*	.006*	.005*	.003*	0.001	-0.001	$QE_x > 0 \; \forall \; x$
< High School	.032*	.021*	.013*	.009*	.007*	.005*	.014*	.002*	0.001	$QE_x < 0 \; \forall \; x$
High School Grad	0.004	0.003	0.002	0.001	0.001	0	0.001	0	0	-
Some Post Secondary	.016*	.010*	.008*	0.006*	.005*	.004*	.003*	003*	.002*	$QE_x > 0 \; \forall \; x$
Post Secondary Grad	-.020*	-.010*	-.005*	-0.003	-0.001	0	0	0	0	$QE_x < 0 \; \forall \; x$
Immigrant	-.016*	-.011*	-.012*	-.009*	-.006*	-0.004	-0.003	-.003*	-0.002	$QE_x < 0 \; \forall \; x$
Prediction Error Statistics:	SD	0.137		1st percentile:	0.348		99th percentile:	0.979		

*p-value of quantile effect < 0.05

Appendix C

Table A3 - Decomposition Results - Direct Effects for SUN=YES with reasons

Characteristic	QE_{10}	QE_{20}	QE_{30}	QE_{40}	QE_{50}	QE_{60}	QE_{70}	QE_{80}	QE_{90}	Dominance Test
Male	-.051*	-.032*	-.028*	-.021*	-.015*	-.013*	-.012*	-.009*	-.005*	$QE_x<0 \; \forall \; x$
Income < 15	.130*	.132*	.114*	.093*	.074*	.052*	.042*	.027*	.016*	$QE_x > 0 \; \forall \; x$
Income [15-20)	.075*	.061*	.054*	.042*	.031*	.025*	.025*	.022*	.010*	$QE_x > 0 \; \forall \; x$

Income [20-30)	.048*	.049*	.045*	.036*	.028*	.021*	.014*	0.009	0.006	$QE_x > 0 \; \forall x$
Income [30-40)	0.029	0.023	0.015	0.012	0.01	0.009	.008*	.007*	0.003	-
Income [40-50)	0.009	0.004	0.005	0.004	0.002	0.002	0.002	0.002	0.001	-
Income [50-60)	0	-0.004	-0.01	-0.009	-0.007	-0.005	-0.002	0	0.002	-
Income [60-80)	-.050*	-.027*	-.016*	-0.01	-0.006	-0.003	-0.001	0	0.002	$QE_x<0 \; \forall x$
Income $\geq$ 80	-.061*	-.044*	-.033*	-.022*	-.017*	-.014*	-.012*	-.007*	-0.001	$QE_x < 0 \; \forall x$
White	0.005	0.004	0.002	-0.002	-0.001	0.001	0.002	0.001	-0.004	-
Black	-.079*	-0.034	-0.016	0	0.004	0.007	0.009	0.004	0.005	$QE_x \leq 0 \; \forall x$
Arabic	0.002	.061*	.061*	.060*	.057*	.048*	.044*	.036*	0.02	$QE_x \geq 0 \; \forall x$
East Asian	-.119*	-.075*	-.047*	-.030*	-.021*	-.017*	-.015*	-.010*	-0.004	$QE_x <0 \; \forall x$
South Asian	-.060*	-0.034	-0.019	-0.016	-0.015	-0.008	-0.001	-0.002	0	$QE_x < 0 \; \forall x$
West Asian	-0.049	-0.049	-0.045	-0.049	-.041*	-.038*	-.023*	-0.014	-0.002	$QE_x \leq 0 \; \forall x$
Latin American	0.074	0.026	0.012	0.014	0.013	0.013	0.017	0.007	0.014	-
Other	.063*	.051*	.036*	0.021	0.011	0.002	0	0	0.004	$QE_x>0 \; \forall x$
Married	-0.009	-0.008	-.011*	-0.008	-0.006	-.006*	-.006*	-.007*	-.004*	$QE_x< 0 \; \forall x$
Common Law	0.005	0.011	.019*	.019*	.017*	.017*	.018*	.017*	.016*	$QE_x > 0 \; \forall x$
Widowed	-0.073	-.098*	-.088*	-.073*	-.063*	-.056*	-.049*	-.040*	-.030*	$QE_x < 0 \; \forall x$
Separated	0.045	0.033	0.029	0.024	0.02	0.013	0.008	0.005	0.003	-
Divorced	.076*	.076*	.063*	.051*	.033*	.018*	0.012	0.012	0.004	$QE_x > 0 \; \forall x$
Single	-.029*	-0.016	-0.01	-0.005	-0.003	-0.003	0	0.002	.003*	$QE_x \leq 0 \; \forall x$
< High School	0.003	0.003	0	-0.003	-0.005	-.008*	-.009*	-.010*	-.007 *	$QE_x < 0 \; \forall x$
High School Grad	0.001	0.01	0.01	.010*	0.008	.007*	0.005	0.004	0.004	-
Some Post Secondary	-0.002	-0.004	-0.002	0.001	-0.003	-0.001	0.002	0.002	0.002	-
Post Secondary Grad	-.020*	-0.011	-0.01	-0.008	-0.006	-0.003	-0.001	0.001	.004*	$QE_x \geq 0 \; \forall x$
Immigrant	0.015	-0.001	0.001	0.006	0.006	0.004	0.004	.005*	.004*	$QE_x \geq 0 \; \forall x$

Prediction Error Statistics:	SD	0.137	1st percentile:	0.348	99th percentile:	0.979

*p-value of quantile effect < 0.05

Fig. 1: Distributions over expectations for care