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Oh Brother How Art Thou? The 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, be satisfied. Using an administrative dataset and a set of conditions that suggest unmet need, we evaluate the proposition that propensity to report unmet need does not vary along socio-economic status. The results are further validated using the Canadian Community Health Survey. Subsequent discussions frame the results within a set of priors about inequality. We find that the assumption of independence between reporting and socio-economic status is not satisfied. Many of the groups found to have less access in previous studies seem to have a higher propensity to report unmet need. The results of this research suggest that, in its present incarnation, survey data on self-assessed unmet need does not adequately measure what much of the academic literature has assumed it does.

Introduction

Research in equality of access is often based on utilization methods, conditioning on 'need' to establish conclusions about fairness in health systems. Health conditions are regressed on utilization and the differences between predicted and actual utilizations are regressed on socio-economic status to determine disparities in access (Van Doorslaer et al. 2004). Mooney (2009) points out that the utilization method rests on the assumption that socio-economic status is independent of preferences for healthcare. Essentially, assuming that utilization studies will result in an accurate description of the state of equality of access in a given country necessarily requires the assumption that, given equality of access, equality of outcome will follow. While this independence assumption could be true, there is no empirical evidence to support it. The consequences of non-independence can include spurious findings where inequality is predicted when none exists, a result formalized mathematically in Gibson et al. (2017). SUN (self-assessed unmet need) was therein proposed as a companion measure to help address this issue. In survey data, SUN is derived from a question such as "During the past 12 months, was there ever a time when you felt that you needed health care but you/he/she didn't receive it?"[1]. In this paper we rhetorically use unmet need distinctly from SUN. Unmet need will refer to "the truth", whether the person in question is receiving appropriate care in the appropriate amount or not. SUN, in contrast, is the belief about unmet need reported by a potentially uninformed survey respondent. This belief may or may not be perfectly consistent with unmet need. SUN, therefore, is a product of the true unmet need and some error in its observation in the data which may or may not be idiosyncratic. The success of SUN as a means to bolster the conclusions of utilization studies requires that it meet two criteria: SUN must have some empirical link to health (ie. it must not be completely subjective), and patterns in propensity to report SUN across socio-economic groups must be established and eliminated.The first of these criteria is established in Canadian data in Gibson et al. (2017) (with similar results being seen in France (Dourgnon et al. 2010) and specific sub-populations in China (Zhen et al. 2015)). This suggests the need for the second criterion to be investigated; the aim of this article. To study socio-economic correlates of SUN, we assess differences in the distributions of the error term in a propensity score estimate using SUN reported in the Canadian Community Health Survey (CCHS) across socio-economic statuses. We subsequently employ the CCHS linked to hospital discharge records from the Ontario Health Insurance Plan (OHIP) to establish the propensity to report unmet need for those admitted to hospital with a condition that ought to

[1]This specific wording is from the Canadian Community Health Survey used in this analysis.

be treated by a primary care physician.

SUN research has found that low income, those with higher levels of education, women, and recent immigrants have been found to report higher rates of unmet need (Koolman 2007, Åhs & Westerling 2006, Shi & Stevens 2005, Newacheck et al. 2003, Chen & Hou 2001, Himmelstein & Woolhandler 1995). These studies have taken the reports of SUN as given or indicating true unmet need. We propose that there is room for some error in the reporting and that if this error varies with socio-economic status then spurious correlations between SUN and socio-economic status could be found. This spurious correlation, if it exists, can result in improper redistribution of resources to target populations based an overstated level of SUN relative to unmet need for some groups. In this paper we test whether certain subpopulations systematically report more unmet need (the error component of their SUN reports is systematically larger/smaller.) We find evidence that certain subgroups who have been found in the literature to report more SUN *are also more likely to report SUN*. 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

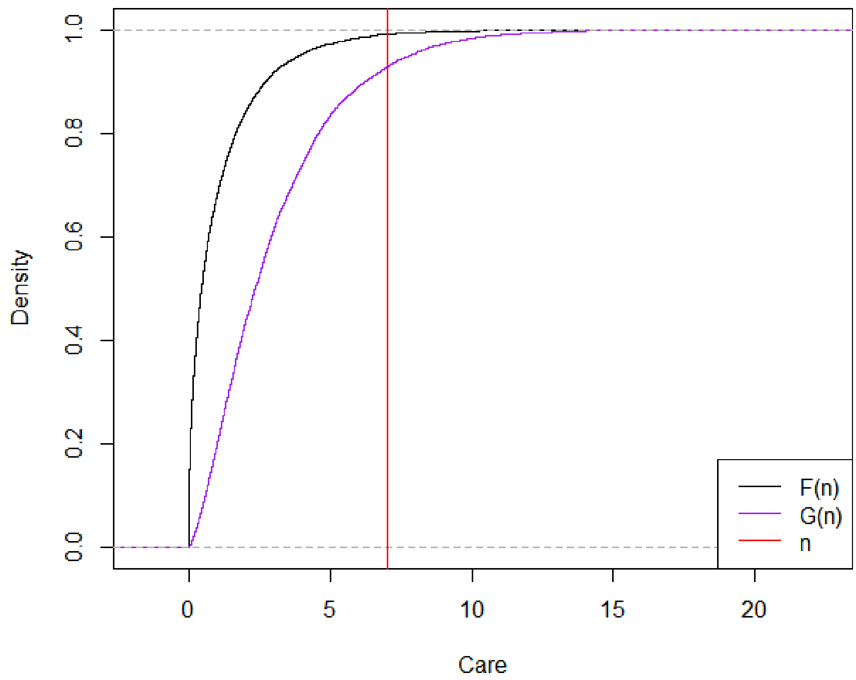
Unmet need has been divided into five categories by Allin et al. (2010) (see table 1). Unmet need could be misreported in any of these categories through either a false positive (SUN is reported while unmet need doesn't exist) or false negative (there is an unmet need, but no report of SUN). For many of these categories, differences in perspective will generate a different response depending on the individual being asked about unmet need. Although testing many of these types is beyond the capabilities of our data, we are able to provide evidence that there exists differential reporting in the false negatives for type 4 unmet need (care received is inappropriate). The difficulty in assessing true unmet need arises from the fact that access to healthcare is latent until need arises and that assessing the veracity of any unmet need report is beyond the capabilities of most datasets.

In the survey, SUN is 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 didn't receive it?" [Statistics Canada]. A positive response to this question will prompt further questioning about the reason and type of unmet need. Three types of unmet need have been established in the Canadian data by Chen & Hou (2001): accessibility (cost too great, transportation problem); acceptability (too busy, didn't get around to it, felt it would be inadequate, decided not to seek care, didn't know where to go, dislike doctors, personal or family responsibilities, language problems, "other" is classified here); and availability (wait time too long, not available when required, not available in area). Reasons for unmet need include injury, mental health, missed checkup, and physical ailment. In both type and reason for unmet need, multiple responses are permissible. Since we will eventually be using administrative Ontario claims data it is worth noting that in Ontario reports of unmet need are lower than the Canadian average; especially in the categories of availability and accessibility. Of interest is whether the biases we might observe in responses to this question will be expected in other surveys of this nature. The most common of these is the EU-SILC: question PH-040 asks about the unmet need for medical examinations or treatments. Since the survey occurs across European countries (and thus languages), the specific wording of the question can't be directly compared to Canada. The coding of the response in the survey, however, 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". 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 2011). In the US, questions tend towards a similar wording. In a National Center for Health Statistics survey on older Americans "Respondents were asked if anyone in the family was unable to obtain needed medical services at least once in the last 12 months." (Cohen et al. 1997). Again, we see the time frame and generic nature of the 'care' being described. A key difference in the American and EU wordings from the Canadian wording lies in the word 'feel' present only in the Canadian survey. This may elicit a *more* subjective response to the question, although further work will be necessary to establish whether this is indeed the case since respondents' perceptions are the source of the data in all cases. 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 any disparities exist across surveys.

Theoretical Framework

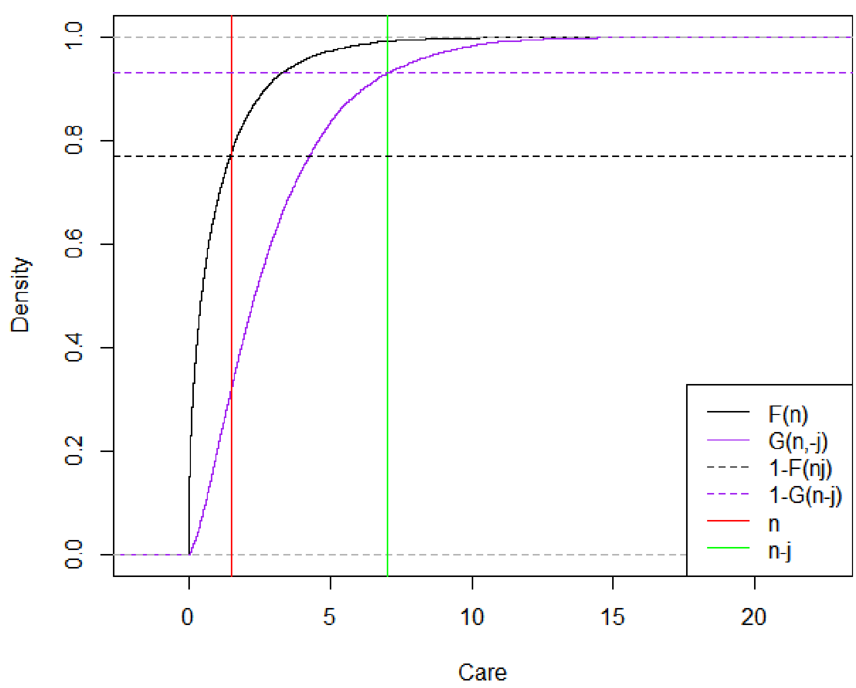
Since the amount of need will obviously depend on the individual's health status, the following discussion of population use, care and expectation levels is always to be assumed to be conditional on health. Suppose that the expectations for care are distributed over number of visits for the general population with distribution $f(n)$. For a given level of care n all those whose expectations for care are greater than n will report unmet need (i.e. $\int_n^\infty f(n)dn$ corresponding to a percentage $(1-(F(n))))$. Traditional 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 $f(n)$. 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.

Fig. 2: Distributions over expectations for care



Given a level of care (n), share $1 - F(n)$ of the general population will feel that this level of care is inadequate and share $1 - G(n)$ of subpopulation 'j' will feel the level of care is inadequate. Given the assumptions about the subpopulation we made in defining $G(n)$ we should observe a higher percentage of the subpopulation with SUN. Suppose we now consider differences in care between the two groups with the subpopulation receiving a new level of care n_j greater than that received by the general population n_{-j}, where "$-j$" denotes all groups excluding j (see figure 2).

Fig. 3: Expectations of care when provision is different



Which group reports more depends on whether $F(n_j)$ is greater than or less than $G(n_{-j})$; although in our example we depict $G(n_{-j})$ as being higher at the example levels of care. What is clear is that the differential in reporting is inconsistent with the amount of care used. Finally, we should note that the marginal person who is reporting unmet need (the person whose expectations are exactly n_j or n_{-j}) has a higher expectation of care and thus a higher level of observed care assuming that people stop consuming healthcare when their expectations are satisfied. 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.

The theoretical results from Gibson et al. (2017) suggest that unmet need is important since it can be used to verify predictions from potentially inconsistent utilization-based studies. The unmet need considered in their framework presupposes an empirically verifiable "unmet need", or more simply, SUN as simply a proxy for true but unobserved unmet need with some stochastic element. In this analysis, we are interested in the relative position of the two cumulative densities related to expectations about care. Discovering the differences between the distributions of expectations between two groups requires carefully conditioning on both health status and amount of care and looking at the reports of unmet need between the two subgroups. 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 socio-economic status 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

$$\hat{n}_{ij} < n_{ij}. \tag{2}$$

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 (ie. preferences are independent of socio-economic status.) 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:

$$SUN = \mathbf{I}(f(h_{ij}) + \epsilon_i > \hat{n}_{ij}) \tag{3}$$

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 socio-economic status however, equation three can be rewritten as

$$SUN = \mathbf{I}(\epsilon_{ij} > \hat{n}_{ij} - f(h_{ij})). \tag{4}$$

SUN will now be seen to vary with socio-economic status 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 empirical exercises. In the first exercise, we attempt to describe the distribution of ϵ_{ij} relative to $\epsilon_{i,-j}$. Second, we condition on a value of $\hat{n} - f(h_{ij})$ that would generally be deemed unsatisfactory by a health professional, and attempt to test whether ϵ_{ij} has a different mean from $\epsilon_{i(-j)}$.

Empirical Framework

Propensity analysis

To generalize our investigation into differential reporting rates, we first estimate the population average distribution of utilization-standardized unmet need. Using this estimated function we are able to identify ϵ_{ij} by subtracting $\hat{SUN}$ from SUN_i where $\hat{SUN}$ is the fitted value based on the estimated equation. We then examine the distribution of ϵ_j by regressing the values on socio-economic indicators using the unconditional quantile regression methods of Chernozhukov et al. (2013) implemented using the cdeco command in Stata. 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 ϵ_j and ϵ_{-j} may be partially driven by differences in other observable factors. By using the counterfactual analysis, we are able to 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 (ie. our calculated scores can be a composite of any bias that results in a deviation from the population average reporting behaviour). For example, if we were able to condition on desired healthcare n_{ij} *and* observed healthcare $\hat{n}_{ij}$ we would be able to describe the resulting disparity in unmet need that was orthogonal to quantity-expectation bias. While this analysis 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 reseach has been devoted to the topic of reporting bias in health surveys regarding self-assessed measures of health (see for example Black et al. (2017), Hernández-Quevedo et al. (2005), Benítez-Silva et al. (2004), Kerkhofs & Lindeboom (1995)) with mixed findings. While, to the best of our knowledge, noone has yet looked at biases in SUN, the findings from other work suggest that we will: (a) find some bias in the SUN measure, and (b) be unable to estimate the exact value of this bias due to biases in other self-reported variables. We describe unmet need reporting behaviour relative to the average individual, which suggests that for a given level of health and care some groups may report more than others. What we estimate first is

$$Pr(SUN = 1|\hat{n}_{ij}, h_{ij}). \tag{5}$$

This provides us the population 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. Since the distribution of error terms 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 (ie. those whose survey indicated that they had SUN) only. 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, Chernozhukov et al. (2013) describe three potential counterfactual scenarios: 1) The difference between group j and -j observed by changing the conditional distribution (given a set of controls how does the distribution of outcomes differ?), 2) The difference observed by changing the covariate distribution (given the same distribution of controls, how does the distribution of outcomes differ?), 3) The total difference (the sum of 1 and 2). The first counterfactual scenario reflects what we might think of as differences in effects of covariates between groups. For example, how does being male relate to reporting behaviour independent of all other socio-economic statuses. The second counterfactual scenario reflects the effect of differences in covariate distributions. For example, if immigrants were 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 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 we discuss one and two separately. Finally, we note that any conclusions are not causally attributable to membership in the group, but rather just a pattern of reporting differences observed on average between groups.

Recall 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. For this analysis, conditioning on the observed quantity of care and health status will be sufficient for the preliminary investigation of over-reporting and under-reporting among people.

In the estimation of the propensity to report unmet need, 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 both the model's apparent and true error. *Apparent error* is an in-sample measure of goodness-of-fit. The smaller the apparent error, the better the model is at fitting the original data points. The canonical example of in-sample goodness-of-fit is the R^2 from ordinary least squares regression. As the estimation of the propensity to report unmet need is a binary choice model, in-sample goodness-of-fit was measured by pseudo-R^2

(McFadden 1973). *True error* is a measure of the model's inability to fit data points outside the given sample. A low apparent error may give a 'falsely optimistic' view of the model's predictability (Efron 1986). To measure the out-of-sample fit, we employ k-fold cross-validation as implemented in (Daniels 2012).

Cross-validation is a process where a subsample of the data is removed prior to fitting the model. The remaining subsample, known as the training data, is used to estimate the model's parameters. Once the model is fitted, it used on the removed data, or evaluation data, to assess the model's out-of-sample performance (Refaeilzadeh et al. 2009). K-fold cross-validation begins by splitting the sample into k equally sized subsamples. Next, the k subsamples are sequentially selected as the evaluation dataset, the model is fit using the remaining $k-1$ subsamples as the training data. The final step is to run the model with the evaluation data and compute the pseudo-R^2. This process is repeated until each of the k subsamples is used as the evaluation data resulting in k pseudo-R^2 values from each iteration of the cross-validation process. In our analysis, we set $k = 25$ and we compared the out-of-sample performance of the model specifications based on the average value of the pseudo-R^2s.

We considered four sets of predictor variables, regressing self-reported unmet need on each set using both the probit and logit estimators. In our estimation, SUN is modelled as a function of age, health region (administrative regions for health funding in Canada), health, and health care variables. Let X denote a vector of predictor variables used in each model specification. The variables in X we consider are activity restrictions, body mass index (BMI), type of smoker, comorbid conditions, whether the respondent has a family doctor, the respondent's health region, age, and province of residence. Activity restriction is a binary factor variable which takes a value of 1 if the respondent has difficulties with activities and 0 otherwise. BMI, which is computed as $|\text{BMI}-21.8|$ (21.8 is the midpoint of a "healthy" BMI), and we don't expect unmet need to simply be a function of increasing BMI. Type of smoker takes on four values: daily, occasional, former (someone who has smoked 100 cigarettes in their life but does not presently smoke), and never. Chronic conditions considered in our analysis are 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. These take a value of 1 if the respondent suffers from the given condition and zero otherwise. To attempt to condition on supply side factors for unmet need, we use health region effects. Observed utilization is measured by the "number of consultations with medical professionals" (eg. physicians, nurses, but excluding eye and dental professionals), denoted by Qmd.

We begin by entering all continuous predictors in a linear fashion, and then introduce some marginal changes in specification, where our goal is to maximize the pseudo-R^2 for both the in-sample and out-of-sample evaluation methods. Age is popular control variable in determining patterns of health care utilization and is often assumed to have a quadratic relationship with the probability of using health care goods and services. The hypothesis is that this probability is higher for the very young and seniors compared to those between the ages of 18 and 64 years Mulvale & Hurley (2008). We extend this idea by assuming that those who are more likely to require heath care services are more likely to experience an unmet need. For the number of visits to a healthcare professional, we assume that as individuals visit a physician more frequently, the likelihood of experiencing unmet need decreases. Furthermore, we assume that as the number of visits increase, the probability of experiencing an unmet need decreases but at a smaller rate. To impose this relationship, we include the natural log of the number of visits to healthcare professionals ($-\ln(n)$ would give such relationship). The four sets of variables used to predict the propensity to report unmet need are {X, Qmd, age}, {X, Qmd, age, age^2}, {X, ln(Qmd+1), age}, {X, ln(Qmd+1), age, age^2} (See Table 3).

Following this, we conduct the decomposition analysis at the deciles of the prediction error. In the Chernozhukov et al. (2013) 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 (eg. instead of being a continuous measure, income is categorized in a series of binary variables 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 socio-economic status variable is positive at all deciles for those reporting SUN (negative for people not reporting SUN). In the case of actual reports of SUN, stochastic dominance where $QE_X > 0 \forall X$ suggests the situation in figure 1 where the subpopulation assumes the distribution $G(n)$. Second order dominance is more difficult to conceptualize. Consider the case of those who actually report SUN. A set of positive coefficients at the higher deciles with negative coefficients at the lower deciles suggests more accurate reporting (ie. those with a low predicted value do not report and those with a high predicted value often do.) A set of negative coefficients at higher deciles with positive coefficients at lower deciles suggests the opposite, that the distribution of prediction errors is compressed because there are many reports of SUN at low predicted values. However, high/low variances could also occur as a result of a subpopulation that is particularly healthy (in the case of a compressed distribution) or particularly unhealthy (expanded distribution), although a conditional quantile regression on the predicted score did not suggest any serious outliers among socio-economic groups' predicted SUN to suggest that some groups were vastly healthier than others (see table 6). Regardless, we observe second order dominance only in indirect effects which we consider to be of second order importance.

The bootstrap stochastic dominance test we employ follows from Linton et al. (2010) where the null hypothesis is that the estimated quantile effect is smaller than (greater than) the counterfactual distribution of quantile effects eg ($H_0 : QE_x < 0\forall X \; H_a : QE_x \geq 0 \text{for some} X$). If these distributions overlap sufficiently, it is possible to fail to reject both $QE_x < 0\forall X$ and $QE_x > 0\forall X$ while failing to reject $QE_x = 0\forall X$. Thus, table 7 reports stochastic dominance as follows: if we fail to reject one form of stochastic dominance, say, $H_0 : QE_x < 0\forall X$, but we *can* reject $H_0 : QE_x = 0\forall X$ and $H_0 : QE_x > 0\forall X$ we simply report $QE_x < 0\forall X$. If we fail to reject $QE_x < 0\forall X$ *and* $QE_x = 0\forall X$, we report $QE_x \leq 0\forall X$. 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.

Ambulatory Care Sensitive Conditions

Because our first set of results will be somewhat unreliable if the reporting bias in self-assessed unmet need is highly correlated with the reporting bias in our self-reported controls, we undertake a second exercise to identify an externally validated metric of unmet need.

Ambulatory Care Sensitive Conditions (hereafter ACSC) are conditions whose most appropriate treatment occurs with the primary care physician. More specifically, the Canadian Institute for Health Information (hereafter 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, p.89). We propose that emergency room hospitalization for an ACSC reflects an unmet need for primary care where either the quality or amount is insufficient. A similar interpretation is used to investigate access to primary care in Grignon et al. (2015). This would thus fall under SUN type 4 where experts feel that the type of care received is inappropriate, and is the only determinable true positive that exists in the unmet need framework since it is the only category that relies on external validation. Given that the people in question are still receiving care (to be in this part of the analysis they had to be admitted to an acute care facility with an ACSC) the rate of unmet need report 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 (or at least not substantially different between the groups), although the nature of these conditions does not eliminate the possibility that some of these hospitalizations are truly unavoidable and that no unmet need exists in some of the cases. Given these assumptions, comparing the mean rate of SUN between two groups and finding a difference would suggest that there is some difference that leads one group to report unmet need 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 in an area. For example, if women and men tend to report unmet need 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 reporting rates as given. Within the theoretical model, this will test whether, for a level of $\hat{N}$ that is below an expert assigned threshold for SUN, there is a gap between $f(\hat{N})$ and $g(\hat{N})$.

We use two separate definitions of ACSC: the first is from Caminal et al. (2004), and the second directly from CIHI (*Technical Note: Ambulatory Care Sensitive Conditions* 2014), although many such lists of ACSC conditions exist (see for example Grignon et al. (2015), Walker et al. (2009), Brown et al. (2001), Billings et al. (1996).) An important 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 (ex. Young et al. (2016), Falik et al. (2006), Solberg et al. (1990)). 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. The next criterion is that hospitalization be avoidable even when the condition is present as this is an additional indicator that received care is inappropriate (even at the point of hospitalization in some cases) diminishing the potential for preferences for delaying care to impact our results. We are less concerned about the prevalence of the disease (as some exceedingly rare conditions simply won't appear in our sample) and consistency in diagnostic coding (as our data all come from the same province.) By CIHI's definitions, 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 this criterion also. We use the hospital discharge database (described in the next section) and match the hospital records for the 12 months prior to an individual's survey date since the SUN question specifies the last 12 months as a timeframe. Given that an ACSC generally represents an unmet need and that 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 socio-economic statuses. If we are to reject differences in reporting behaviour we should not observe differences in reporting rates among our ACSC hospitalized. The higher the reporting among a particular subpopulation, the more accurate that particular subgroup is in self-assessment of unmet need, given our assumptions about ACSC hospitalizations. We will couch the discussion as one group having a higher propensity to report (which, when conditioning on poor health as we are, is desirable, but need not remain so at the bottom of the distribution of actual unmet need - ex. when true unmet need is zero we would hope that SUN is also zero.)

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 & Hou (2001) since they are using the same dataset during approximately the same time period) to evaluate whether this difference is at least partly explained by propensity to report. It could be argued that the results of the analysis described above are driven not by diffences in propensity to self-assess unmet need, but rather by a difference in the distribution of diseases between groups even among those with an ACSC. To address this criticism, we further identify the set of conditions that are not disproportionately observed in one group. With the full list of conditions we proceed to do the following: we count only those with a non-correlated condition (ie. we cannot predict the socioeconomic variable at a 5% significance level using the disease as the only predictor in a linear probability model) and use this further restricted subsample to recalculate our test statistic. For example, when comparing men and women, we see that urinary tract infections and anaemia are more common among women and upper respiratory tract diseases are more common in men. We exclude anaemia, urinary tract infections and upper respiratory tract diseases when recomputing the ACSC list to reevaluate differences in our sample's propensity to report. The idea behind this method is to compress the conditions list to remove the influence of the distribution of diseases on the propensity to report. An unfortunate effect of this change is that in some cases, the sample size is reduced to the point where a statistically significant result becomes impossible. In the case of income, all diseases are removed, and no robust-ACSC-list conclusions are possible. A large number of removed conditions suggests a higher likelihood of the results being driven by the distributional differences. The number of diseases removed and the resulting change in p-value, however, cannot provide conclusive evidence of the importance of those specific conditions to the statistical significance since the observations removed would serve to decrease degrees of freedom even if they did not disproportionately effect a change in the reporting behaviour in the new sample.

Data

Our ACSC sample arises from a self-selected group of respondents to the CCHS (Canadian Community Health Survey) in 2001, 2003 and 2005 who agreed to have their survey responses linked to the administrative OHIP data. We are particularly interested in hospital discharge data which 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. Since it is optional to agree to the administrative data linkage, concern about self-selection biasing our results prompted us to attempt to determine if our sample was different than the CCHS as a whole. Further examination revealed that the sample means of our regressor variables were not vastly different from the sample means available in the public use files (representative of the whole CCHS).

As we have no real means of treating a selection problem if it exists and we don't find any evidence to suggest that sharing of administrative data was sorted on observables, we proceed with the analysis without further consideration of this potential issue.

The CCHS is meant to cover 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 constitutes only a few individuals leaving the original dataset. Since ACSC hospitalizations are very rare, we naturally do not observe many cases where an ACSC hospitalization coincides with being sampled for the CCHS within one year. Our sample size for the ACSC analysis is 158 and should not be considered representative of the Canadian population. Table 10 shows the proportions and means of the socio-economic variables in the ACSC sample.

For the conditional quantile analysis, we expand the set of survey years, including 2009-2013 in the data (since the intervening 2006-2008 data do not ask about unmet need). 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. Summary statistics in table 4 show the population statistics of the estimation sample (i.e. with the provided survey weights incorporated to show the population over which the estimation takes place). We show the overall proportion of the population in the subsample, the proportion of the subsample reporting unmet need, and the average HUI3 for the subpopulation. HUI3 -Health Utility Index (Horsman et al. 2003)- is a single number that is 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) increase in health as education increases. 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 tends to be correlated with age, these unconditional averages should not be taken at face value.

Result

Propensities in CCHS Data

Table 3 displays the results from in-sample and out-of-sample performance measures. For each set of predictor variables, the probit specification holds a slight advantage over the logit specification for both in-sample and out-of-sample performance indicators. The model with the best fit is the probit specification regressing $\{X,\ln(\text{Qmd}),\text{Age}^2\}$ on SUN with an average out-of-sample pseudo-R^2 of 0.0687. While pseudo R^2 is not analogous to OLS' R^2 in that we cannot say that our prediction model explains $\approx$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. This other potential weakness of SUN as an evaluation metric deserves further scrutiny, however, we will not address it further in this paper.

Since the error in the propensity model is specified as $SUN(reported) - S\hat{U}N$, for reports of SUN, all the values will be positive. The closer the error term is to zero, the lower the expectations of care must be (i.e. F(n) is smaller on average at that quantile.) Thus, a negative coefficient represents a lower expectation of care, and a positive coefficient, a greater expectation of care. Statistical tests can help us make sense of the reporting behaviour of different groups. First, we can test whether the coefficients at the deciles are all negative or all positive. This would suggest that a group has higher or lower expectations of care for all levels of predicted SUN. If this is not the case, yet there are some deciles where the coefficient is different from zero, this suggests that the propensity to report diverges as reports become more or less likely (ie. the accuracy of reporting depends on the predicted likelihood of reporting). In table 6 we present 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 socio-economic status. 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. The quantile regression provides some preliminary evidence that baseline reports need to be conditioned on health status in order to properly account for differences in reporting, and that studies looking at rates of unmet need in a population may be merely re-establishing the social determinants of health rather than differences in access to care. We see that trends in reporting behaviour seen in table 4 map to the predictions of our health and usage regression in 6 suggesting that health status can predict reporting behaviour. Two exceptions to this are those who are widowed or separated who report much more unmet need than the average despite having predicted probabilities not too far off (or lower) than the 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. While the comparison of the predictions to the reporting data is promising in terms of broad patterns, a more thorough investigation of the errors in the prediction is needed to determine whether reporting behaviour is systematically different across socio-economic statuses.

Table 7 shows the effect of coefficients conditioning on the distribution of the other covariates in the anaylsis. This eliminates the "indirect effect" of differences in the distributions of other factors between any two groups being considered. Table 8 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 first coefficient can be thought of as the effect on the likelihood of reporting because the individual has characteristic 'x', the second 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.... Despite the causal language in the preceding explanation, this analysis does not suggest that reporting behaviour is causally related to socio-economic characteristics. Both of these pieces of information 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 reported SUN could also be the result of a joint distributional effect rather than a difference in experience between two separate groups. A number of differences exist in the position of the distribution of expectations. Notably, here we find that men's reporting behaviour first order stochastically dominates that of women, reporting behaviour seems to show a gradient with income with low income respondents being first order dominated by higher income . While this reporting over income may seem puzzling to those who believe knowledge of the system may be a factor in reporting, it is worth noting that the income decomposition conditions on education, and the education pattern is as expected with post-secondary grads being first-order dominated by other education levels, and those without high school first order dominating those with at least high school. Black and East Asian respondents first order dominate other racial groups, while Arabs are first order dominated. Comparing this to the results in table 8 shows 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). Policy-makers attempting to correct the distribution of health-care resources based on reports of unmet need will tend to overadjust for the former group and underadjust for the latter.

An alternative possible explanation for the results is that the types of unmet need differ across groups (a type of misspecification of the first stage probit regression.) If this were the case, we could understand the difference in socio-economic groups as being not the result of reporting bias. Like Chen & Hou (2001) we separate unmet need into 3 types (acceptability, accessibility, and availability). We use these categorizations to try to identify a difference in types across socio-economic groups that might explain the differences in reporting. We do see some evidence that the prediction error is correlated with the types of unmet need. This suggests that those in worse health are reporting different types of unmet need from those in better health. Specifically, 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. 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 propensity to report 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 in the type of unmet need to the decomposition. 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 propensities. In most socio-economic categories observed reporting does not change between specifications. Only one category loses significance (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 can explain part of the results from pooled SUN. The results of this decomposition can be found in table 9.

Propensities Among ACSC Hospitalized

We observe evidence that the results of previous studies may be biased by differences in the propensity to report. In table 11 we see the proportions of each group reporting SUN and the p-value of a one sided test for a difference in this proportion of reporters or mean values between reporters and non-reporters (recall that the test is in the direction of inequality proposed in Chen & Hou (2001)). A low p-value suggests that there is a tendency for the group previously thought of as having unequal access as having a greater propensity to report unmet need. A moderate p-value would indicate that there is not likely to be much difference between the two groups' propensities; differences attributed to unequal access in previous work are unlikely to be explained by differences in propensities to reports. We find evidence that reporting propensity increases with education, and that singles have a higher likelihood of reporting. There is some evidence that women have a higher propensity to report than men. We also find that there is no difference in reporting behaviour between immigrants and non-immigrants. These findings relate closely to the propensity analysis where we similarly show that women are more likely to report than men, and post-secondary grads more likely than other education levels. Incongruent findings can be reconciled by considering that the ACSC results do not control for indirect effects, thus, the fact that higher incomes are more likely to report in the ACSC analysis and less likely in the propensity analysis, can be attributed to the higher likelihood of reporting as education increases, and the positive correlation between education and income. Similarly, the non-finding for immigrants in the ACSC analysis can be summarized by a higher likelihood of reporting among immigrants, but a lower likelihood of reporting for other socio-economic groups that are disproportionately likely to be immigrants.

The results of these analyses suggest that, in many cases, the literature may have misidentified an inequality that does not really exist; while in others, the differences in rates of unmet need are not attributable to differences in reporting behaviour.

Conclusions

We have shown that the propensity to report SUN when asked by a surveyor varies by socio-economic status. This result has been shown in this paper using both internal (to the survey) and external data to validate the reports. Because of these differences in reporting behaviours, it is important for policy-makers using these or similar SUN questions to evaluate their effectiveness in measuring access to healthcare to adjust the questions to minimize the response bias identified here. 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 need in the population. Future work should focus on ensuring that surveys on health more accurately measure unmet need with less non-need related variation between subpopulations. Alternatively, dispassionate reviews of assessed unmet need (as judged by an expert panel, or ordinary survey respondents) could be applied to the observed data from surveys to determine whether unmet need exists. Until this time, users of SUN should understand that the unmet need they are measuring is often endogenously determined by the socio-economic statuses they are trying to map it to.

Appendix

Table 1: Categories of Unmet Need

Category	Name	Description	Example	Unmet Need Report
1	Unmet-unperceived	Subject doesn't know they need care	Undiagnosed cancer	No
2	Subjective chosen	Knows of need, but elects not to seek care	Taking advil for chronic headaches	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 management	Maybe
5	Subjective expectation-based	Good care received, but patient unsatisfied	Patient expects constant attention during hospital stay	Maybe

Adapted from Allin et al. (2010)

Table 2: ACSC conditions

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

Restrictions and exceptions apply as per Caminal et al. (2004) and *Technical Note: Ambulatory Care Sensitive Conditions* (2014).
We do not observe any hospitalizations for some conditions present in Caminal et al. (2004) these conditions
do not appear in the list.

Table 3: 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
Agesq		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.

Table 4: 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	0.90
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	1.0	18.6	0.89
East Asian	7.0	8.8	0.90
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 5: Probit Regression for Predicting SUN

Health Variable		Coefficient	Standard Error
Self Assessed Health			
	Very Good	0.178*	0.021
	Good	0.334*	0.023
	Fair	0.510*	0.031
	Poor	0.676*	0.048
Age		0.025*	0.002
Age Squared		0.000**	0.000
BMI[1]		-0.004	0.002
Smoking			
	Occasionally	0.014	0.032
	Former	-0.037	0.021
	Never	-0.088	0.020
Chronic Conditions		✓	
Health Regions		✓	

[1] BMI=$|\text{BMI} - 21.8|$

Table 6: 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)	0.010	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		0.000	0.001
Constant		0.046	0.204

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

Table 7: 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
Married	-.007	-.008	-.008	-.007	-.003	-.004	-.005	-.006*	-.003*	$QE_x \leq 0 \forall x$
Common Law	.004	.009	.020*	.020*	.016*	.016*	.017*	.017*	.016*	$QE_x > 0 \forall x$
Widowed	-.073	-.097*	-.089*	-.075*	-.065*	-.057*	-.048*	-.039*	-.031*	$QE_x < 0 \forall x$
Separated	.043	.033	.030	.025	.017	.014	.007	.003	.003	
Divorced	.074*	.081*	.066*	.047*	.031*	.017*	.013*	.012*	.008*	$QE_x > 0 \forall x$
Single	-.031*	-.016	-.010	-.007	-.004	-.005	-.002	.001	.004*	
< High School	.004	.003	-.000	-.003	-.006	-.008*	-.010*	-.011*	-.007 *	$QE_x < 0 \forall x$
High School Grad	.004	.011	.009	.007	.007	.007	.004	.003	.002	-
Some Post Secondary	-.009	-.004	-.002	0.001	-.003	-.001	.001	001	.003	-
Post Secondary Grad	-.020	-.011	-.008	-.007	-.005	-.003	-.000	.002	.006	$QE_x \geq 0 \forall x$
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*	.012	$QE_x > 0 \forall x$
Income [20-30)	.047*	.052*	.043*	.035*	.028*	.021*	.015	.008	.006	$QE_x > 0 \forall x$
Income [30-40)	.032	.023	.017	.012	.010	.009	.009	.007	.003	-
Income [40-50)	.009	.007	.007	.004	.002	.003	.003	.002	.002	-
Income [50-60)	0.00	-.002	-.007	-.009	-.006	-.004	-.001	-.000	.003	-
Income [60-80)	-.050*	-.027*	-.016*	-.010	-.005	-.003	-.001	-.000	0.001	$QE_x < 0 \forall x$
Income $\geq$ 80	-.062*	-.044*	-.032*	-.023*	-.018*	-.013*	-.013*	-.007*	-.005 *	$QE_x < 0 \forall x$
Male	-.050*	-.031*	-.026*	-.021*	-.015*	-.013*	-.012*	-.009*	-.006*	$QE_x < 0 \forall x$
Immigrant	.011	-.002	.002	.007	.006	.004	.004	.005	.004	$QE_x \geq 0 \forall x$
White	.004	.006	.005	.000	.001	.002	.004	.001	-.004	-
Black	-.085*	-.036	-.026	-.006	-.004	-.018	.006	.005	.007	$QE_x < 0 \forall x$
Arabic	.017	.068*	.065*	.058*	.058*	.048*	.045*	.040*	.021	$QE_x > 0 \forall x$
East Asian	-.112*	-.067*	-.045*	-.027*	-.019*	-.016*	-.013*	-.009*	-.004	$QE_x < 0 \forall x$
South Asian	-.060*	-.034	-.016	-.015	-.009	-.001	.000	-.004	.001	$QE_x \leq 0 \forall x$
West Asian	-.042	-.058	-.054	-.050	-.042*	-.038*	-.020	-.014	-.006	$QE_x \leq 0 \forall x$
Latin American	.076	.020	.005	.017	.014	.013	.017	.010	.021	-
Other	.069*	.051*	.035*	.020	.009	.000	-.001	-.000	.004	$QE_x > 0 \forall x$
Standard deviation:	0.137		1st percentile:	0.348		99th percentile:	0.979			

*p-value of quantile effect < 0.05

Table 8: 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
Married	-.043*	-.023*	-.016*	-.011*	-.009*	-.005*	-.004*	-.002*	-.001	$QE_x < 0 \forall x$
Common Law	-.020*	-.008*	-.008*	-.006*	-.004*	-.003*	-.002*	-.002*	-.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*	.001	-.001	$QE_x > 0 \forall x$
< High School	.032*	.021*	.013*	.009*	.007*	.005*	.014*	.002*	.001	$QE_x < 0 \forall x$
High School Grad	.004	.003	.002	.001	.001	.000	.001	.000	-.000	-
Some Post Secondary	.016*	.010*	.008*	0.006*	.005*	.004*	.003*	003*	.002*	$QE_x > 0 \forall x$
Post Secondary Grad	-.020*	-.010*	-.005*	-.003	-.001	-.000	-.000	.000	.000	$QE_x < 0 \forall x$
Income < 15	.023*	.011*	.005	.003	.001	.001	-.000	-.001	-.002	$QE_x > 0 \forall x$
Income [15-20)	.027*	.014*	.008*	.005	.002	.000	-.001	-.002	-.004*	S.O.D
Income [20-30)	.021*	.010*	.007*	.004*	.002	.001	.000	-.000	-.001	$QE_x > 0 \forall x$
Income [30-40)	.008	.004	.004	.002	.002	.001	.001	.000	-.000	-
Income [40-50)	.005	.003	.003	.002	.001	.001	.001	.000	.000	-
Income [50-60)	-.002	-.001	.000	.001	.001	.001	.000	.001	.001	-
Income [60-80)	-.006	-.002	-.001	-.000	.000	.001	.001	.001	.001	$QE_x \geq 0 \forall x$
Income $\geq$ 80	-.020*	-.013	-.012	-.007	-.004	-.003	-.002	-.003	-.002	-
Male	-.009*	-.004	-.002	-.001	-.000	-.000	.000	.001	.001*	S.O.D
Immigrant	-.016*	-.011*	-.012*	-.009*	-.006*	-.004	-.003	-.003*	-.002	$QE_x < 0 \forall x$
White	.002	-.002	.002	.001	-.001	-.001	-.002	-.001	-.000	-
Black	.032*	.024*	.016*	.012*	.009*	.008*	.007*	.006*	.004*	$QE_x > 0 \forall x$
Arabic	.018	.015	.010	.009	.007	.005	.004	.004*	.002	-
East Asian	-.008	-.005	-.005	-.004	-.003*	-.003	-.002	-.002	-.002	-
South Asian	-.011	-.007	-.005	-.004	-.004	-.003	-.003	-.002	-.001	-
West Asian	-.015	-.005	-.003	-.002	-.001	-.001	.001	.002	.002	-
Latin American	.007	.007	.007	.005	.004	.003	.003	.003	.001	-
Other	.023*	.014*	.010*	.007*	.006*	.004*	.003*	.002	.001	$QE_x > 0 \forall x$
Prediction Error Statistics:	Standard deviation:	0.137		1st percentile:	0.348		99th percentile:	0.979		

*p-value of quantile effect < 0.05

Table 9: 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
Married	-.009	-.008	-.011*	-.008	-.006	-.006*	-.006*	-.007*	-.004*	$QE_x < 0 \forall x$
Common Law	.005	.011	.019*	.019*	.017*	.017*	.018*	.017*	.016*	$QE_x > 0 \forall x$
Widowed	-.073	-.098*	-.088*	-.073*	-.063*	-.056*	-.049*	-.040*	-.030*	$QE_x < 0 \forall x$
Separated	.045	.033	.029	.024	.020	.013	.008	.005	.003	-
Divorced	.076*	.076*	.063*	.051*	.033*	.018*	.012	.012	.004	$QE_x > 0 \forall x$
Single	-.029*	-.016	-.010	-.005	-.003	-.003	-.000	.002	.003*	$QE_x \leq 0 \forall x$
< High School	.003	.003	-.000	-.003	-.005	-.008*	-.009*	-.010*	-.007 *	$QE_x < 0 \forall x$
High School Grad	.001	.010	.010	.010*	.008	.007*	.005	.004	.004	-
Some Post Secondary	-.002	-.004	-.002	.001	-.003	-.001	.002	.002	.002	-
Post Secondary Grad	-.020*	-.011	-.010	-.008	-.006	-.003	-.001	.001	.004*	$QE_x \geq 0 \forall x$
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*	.009	.006	$QE_x > 0 \forall x$
Income [30-40)	.029	.023	.015	.012	.010	.009	.008*	.007*	.003	-
Income [40-50)	.009	.004	.005	.004	.002	.002	.002	.002	.001	-
Income [50-60)	.000	-.004	-.010	-.009	-.007	-.005	-.002	-.000	.002	-
Income [60-80)	-.050*	-.027*	-.016*	-.010	-.006	-.003	-.001	-.000	0.002	$QE_x < 0 \forall x$
Income $\geq$ 80	-.061*	-.044*	-.033*	-.022*	-.017*	-.014*	-.012*	-.007*	-.001	$QE_x < 0 \forall x$
Male	-.051*	-.032*	-.028*	-.021*	-.015*	-.013*	-.012*	-.009*	-.005*	$QE_x < 0 \forall x$
Immigrant	.015	-.001	.001	.006	.006	.004	.004	.005*	.004*	$QE_x \geq 0 \forall x$
White	.005	.004	.002	-.002	-.001	.001	.002	.001	-.004	-
Black	-.079*	-.034	-.016	.000	.004	.007	.009	.004	.005	$QE_x \leq 0 \forall x$
Arabic	.002	.061*	.061*	.060*	.057*	.048*	.044*	.036*	.020	$QE_x \geq 0 \forall x$
East Asian	-.119*	-.075*	-.047*	-.030*	-.021*	-.017*	-.015*	-.010*	-.004	$QE_x < 0 \forall x$
South Asian	-.060*	-.034	-.019	-.016	-.015	-.008	-.001	-.002	.000	$QE_x < 0 \forall x$
West Asian	-.049	-.049	-.045	-.049	-.041*	-.038*	-.023*	-.014	-.002	$QE_x \leq 0 \forall x$
Latin American	.074	.026	.012	.014	.013	.013	.017	.007	.014	-
Other	.063*	.051*	.036*	.021	.011	.002	-.000	.000	.004	$QE_x > 0 \forall x$
Standard deviation:	0.137		1st percentile:	0.348		99th percentile:	0.979			

*p-value of quantile effect < 0.05

Table 10: Sample characteristics among CCHS respondents with an ACSC

Characteristic	Proportion
Male	45.6%
High school graduate	15.2%
Some post-secondary	6.3%
Post-secondary grad	35.4%
Immigrant	13.9%
Married/common-law	46.2%
Single	26.6%
Characteristic	**Mean**
Age	54.0
Income	41,700

N=158

Table 11: P-Values to Test ACSC SUN Reporting Behaviour

Socio-economic characteristic	Literature inequality direction	P-value all conditions	CIHI conditions	P-value With excluded conditions	Excluded conditions
Gender	Female > male	0.110	0.348	0.086*	1,2,3,10,12
Education:					
Less than high school	Other> l.t.high school	0.017**	0.039**	0.338	6,8
High school grad	Other > high school grad > l.t.high school	0.350	0.351	0.145	8
Some post-secondary	Post-secondary grad >Some post-secondary >other	0.0**	0.004**	0.011**	1,2,5,7,8,11,12
Post-secondary grad	Post-secondary grad>other	0.08*	0.120	0.074*	3,10,12
Immigrant	Immigrant>non-immigrant	0.65	0.885	0.532	5,8,10,11
Married/common law	Other > married/common law	0.097*	0.193	0.081*	9,12
Widowed/separated/divorced	Widowed/separated/divorced<other	0.485	0.482	0.50	3,4,10
Single	Single>other	0.067*	0.049**	0.226	2,3,5,6,10,12
Income	Higher income > lower income	0.350	0.049**	NA	All
Age	Younger > Older	0.092*	0.851	0.134	1,2,3,6,7,8,9,10

**-Pvalue<.05, *-Pvalue<0.10.

Excluded conditions: 1-Angina, 2-Anaemia, 3-Appendicitis, 4-Bacterial Pneumonia, 5-Bleeding/perforated ulcer, 6-Chronic obstructive pulmonary disorder, 7-Dehydration, 8-Diabetic Complication, 9-Disorder of hydroelectrolyte metabolism, 10-Disease of the Upper Respiratory Tract, 11-Epilepsy, 12-Urinary tract infection.

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